Board Connections, Firm Profitability, and Product Market Actions *

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Abstract

A firm's gross margin increases by 0.8 p.p. after forming a new direct board connection to a product market peer. Gross margin also rises by 0.4 p.p. after a connection is formed to a peer indirectly through a third intermediate firm. Further, using barcode-level data of 2.7 million products, we show that new board connections are related to higher consumer good prices and a greater tendency for market allocation. The effects are stronger when the newly connected peers share corporate customers or have similar business descriptions and hold when controlling for other inter-firm relationships.

Keywords: board of directors, interlocking directorships, product market coordination, antitrust

JEL Classification: G34, G38, L22

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"For too long, our Section 8 enforcement (of the ban on director interlocks among competitors) has essentially been limited to our merger review process. We are ramping up efforts to identify violations across the broader economy, and we will not hesitate to bring Section 8 cases to break up interlocking directorates."

(The DOJ's recent crackdown on director interlocks is an) "effective way of deconcentrating the United States economy today."

- Jonathan Kanter (2022; 2023)

Board connections can enable the flow of information between firms and help coordinate product market actions. Recognizing this, Section 8 of the 1914 Clayton Antitrust Act (the Clayton Act) prohibits firms with substantial overlap in their activities from sharing directors. However, historically, the enforcement of the interlock restrictions has been limited to the context of merger reviews and regulators rarely proactively searched for Section 8 violations in the broader economy (Demblowski, 2022; Kanter, 2022; Sher et al., 2022). Indeed, in an environment of rapidly changing business strategies and product lines, such as in the technology sector, it is challenging to determine which firms compete with one another at a given point in time and more so which of these connections have anti-competitive effects.

The Biden Administration is ramping up efforts to upscale the enforcement of the Clayton Act (Department of Justice, 2022, 2023; Federal Trade Commission, 2023a). While a heated discussion revolving around director interlocks between competing firms is drawing public attention, the evidence on the prevalence of these connections and their implications is rare. In this paper we map the director networks of firms that compete in the product market, explore the anti-competitive role of these networks, and find that the board connections between product market peers are not only common but also associated with higher firm profitability, increased product prices, and greater market allocation.

We define product market peer firms based on the Hoberg-Phillips industry classification (Hoberg and Phillips, 2010, 2016). Combined with BoardEx, we identify instances when such firms are closely linked through the director networks. We consider that two firms have a *direct* board connection if they share a director, and that two firms have an *indirect* board connection if they do not share any board members directly but a member of their respective boards serves on the board of the same intermediate firm. In the twenty-year period of 1999-2018, we identify 1,493 instances of new direct connections to a product market peer and

4,085 instances of new indirect connections to a product market peer. These 1,493 instances of direct board connections between firms that are potentially in the same product market space – according to the Hoberg-Phillips classification – indicate the possibility of imperfect enforcement of the Clayton Act restrictions on board connections between competing firms.

Our first analysis adopts a stacked difference-in-differences model to study the relationship between new product market peer board connections and firm profitability. For every firm that forms a new board connection ("treated" firm), we identify a control firm that is from the same year and industry as the treated firm and is the closest to the treated firm in terms of total assets, gross margin, and Tobin's Q in the year before the formation of board connections ("treatment" or "event"), being indistinguishable in terms of the matching co-variates from the treated firm in the year prior to treatment.

We find that firm profitability significantly increases in the three years after a firm forms a board connection to a product market peer. The increase happens both following a direct and following an indirect connection and is robust to how we measure profitability. In particular, in the three years following an indirect connection, a firm's gross margin, operating margin, and return on assets (ROA) increase by 0.4 p.p., 0.8 p.p., and 0.7 p.p., respectively, suggesting economically significant effects. The estimates are even larger following a direct connection and, respectively, are 0.8 p.p., 1.4 p.p., and 0.9 p.p. We do not see differential pre-existing trends in profitability between the treated and control firms.

Our interpretation that these board connections hinder competition faces a few concerns. First, the changes to the board of directors are likely endogenous to the firm's future prospects. For example, firms that anticipate an improvement in their performance could afford appointing a director who is a better expert in their industry and thus likely connected to a product market peer. Also, the directors of a firm with improving prospects could be more valued in the director labor market and thus more likely to be appointed to the boards of a product market peer. Moreover, board connections can also improve profitability by propagating governance practices that could enhance its internal efficiency or new directors can otherwise benefit the firm with their industry experience (see, e.g., Bouwman (2011)).

We address these concerns by designing tests that focus on new indirect connections that do not arise from the changes in the treated firm's board, in which case the new connections are less likely to be correlated with the treated firm's unobservable future prospects. Moreover, we study granular product-level prices from scanned data to establish that the higher profitability stems from end-consumer price increases. We also provide evidence on convicted collusion cases and report a number of cross-sectional tests

First, we zoom into indirect connection events and isolate a particular subset of connections that are formed because of changes in the boards of an intermediate firm and are not formed because of changes in the board of the treated firm, nor the new appointments of its present directors. That is, we look at cases where the intermediate firm that already shares the director with the treated firm appoints a director from the peer firm, or the peer firm appoints a director from the intermediate firm. We deem these events less likely to be correlated with the treated firm's unobservable future prospects and find a similar increase in treated firms' profitability after forming these indirect connections.

Second, we study firm actions in the product markets using barcode-level price data. Taking advantage of the Nielsen Retail Scanner Data, which contains detailed information on store-specific barcode-level prices and revenues for over 2.7 million consumer goods, we find evidence that new board connections are related to higher product prices. We employ a tightly-specified difference-in-differences model that controls for within-product-category and within-geographic-area time trends and makes use of within-firm-and-time variation for firms that sell in multiple product categories. We find that after board connections are formed, the prices of products in categories that overlap with a firm's newly directly connected peer grow 0.22 p.p. faster per quarter than products of the same firm in categories that do not overlap with its connected peer. This translates into a 0.88 p.p. annualized difference. Indirect connections have smaller yet also statistically significant effects of 0.07 p.p. per quarter.

We also examine how these new board connections relate to market allocation, another type of coordination when firms adjust their product offerings to avoid head-on competition (Belleflamme and Bloch, 2004; Sullivan, 2020; De Leverano, 2023). The Federal Trade Commission (FTC) states that it is "almost always illegal" for firms to divide sales territories or assign customers (Federal Trade Commission, 2022). Based on the cosine similarity between firm-pairs of their geographic distribution of sales, we find that after indirect connections product market peers grow more distant in terms their geographic presence, while we do not observe such behavior after direct connections. We interpret both the rise in price and the drop in similarity as evidence that board connections enable product market coordination. More importantly, these findings suggest that direct and indirect connections facilitate different ways to coordinate firm actions. While the direct connections have much stronger effects on product market prices, the indirect ones are more associated with the tendency to differentiate competing firms' sales portfolios and avoid head-on rivalry.

Third, we document how board connections relate to convicted collusion cases. We find that directly connected firms have a 0.058% probability of having an active convicted collusion case, while it is 0.061% for indirectly connected firms. However, for firms that are more distant in board networks such probability is much lower, e.g., it is 0.017% for firm-pairs with two degrees of separation and 0.004% for firm-pairs with three degrees of separation. This strong associative relationship further suggests that director networks can play a role in facilitating coordination.

Fourth, we examine a series of cross-sectional heterogeneities in the profitability effects. We sort new connections based on a range of firm and firm-pair characteristics and then estimate triple-difference models. We first find that the introduction of Corporate Opportunity Waivers (COWs) in some states, which reduced the legal risks of a director sitting on multiple boards, increases both the frequency and profitability-enhancing effects of board connections. We also show greater effects for connections to peers that share major corporate customers, to peers with higher cosine similarity score in terms of product descriptions, and in industries where the potential benefits of coordination are greater.

We conduct a range of robustness tests. Our findings are robust to controlling for customer-supplier relationship, joint venture, strategic alliance, or linkage via common ownership (Azar, 2022; Gilje et al., 2020; Amel-Zadeh et al., 2022). We also show that non-product market peer board connections do not display such an increase in profitability. In addition, our findings are robust to alternative industry classifications, matching methodologies, and regression specifications. We also find that stock market reaction to connecting director appointments is consistent with enhanced profitability.

This paper provides large-sample evidence that board connections between product market peers are related to better overall profitability, higher product prices, and a greater tendency for market allocation, which are consistent with product market coordination. The literature has been investigating various aspects of board connections between product market peers. Geng et al. (2023) found that reducing legal risks of sharing information outside of the board of directors increases the frequency of director interlocks, which is then associated with higher profit margins and sales revenue. Barone et al. (2022) showed that restricting director interlocks among banks in Italy reduces the interest rates of loans extended by previously interlocked banks. Cabezon and Hoberg (2024) discussed the intellectual property leakage between product market peers connected through the director boards.

Compared to this contemporaneous literature, we look at a broader firm sample and document the pervasiveness of both direct and indirect board connections between product market peers. Moreover and likely more importantly, our multi-product barcode-level data allow us to identify the effects of board connections on both price and non-price coordination, highlighting how direct and indirect connections can have differential effects on actions that firms take in their product markets.

The paper also contributes to the literature on firm conduct and inter-firm linkages that facilitate coordination. Tacit coordination can be achieved with financial disclosure (Bourveau et al., 2020) or executive compensation (Ha et al., 2024). Recent literature has also extensively looked at whether sharing common investors contributes to product market coordination (see, e.g., He and Huang (2017); Azar et al. (2018); Antón et al. (2023); Aslan (2023)). We highlight board connections as one form how tacit coordination in product markets can be facilitated among commonly owned firms but also among firms without common ownership.

In addition, this paper speaks to our understanding of the dual role of directors as both advisors and monitors in a firm (Güner et al., 2008; Adams and Ferreira, 2009; Duchin et al., 2010; Dass et al., 2013; Drobetz et al., 2018; Gopalan et al., 2021) and focuses on how such roles change when the directors can help coordinate product market actions between competing firms. Relatedly, Campello et al. (2017) showed that independent directors suffer personal costs from cartel prosecutions and they take actions to mitigate those costs.

Finally, we add to the literature on social networks and, in particular, on the network of directors. Prior research has documented that this network influences director-level outcomes. Goergen et al. (2019) provided evidence that more connected directors make more profitable insider trades, which corroborates the existence of information exchange between directors. Intintoli et al. (2018) showed that more connected directors have better career prospects. At the firm level, the network of directors enhances firm value (Bakke et al., 2024), affects investment decisions (Fracassi and Tate, 2012; Chuluun et al., 2017), disclosure (Intintoli et al., 2018), and governance policies (Coles et al., 2020; Renneboog and Zhao, 2014; Bouwman, 2011), and is associated with better merger outcomes (Cai and Sevilir, 2012; El-Khatib et al., 2015), more intellectual property leakage (Cabezon and Hoberg, 2024), and greater stock price synchronicity (Khanna and Thomas, 2009). We restrict our attention to connections between product market peers and posit that this economically important class of connections is associated with better firm profitability and product market coordination.

1 Hypothesis Development

Successful coordination among competing firms yields supra-competitive profits, which can exceed their respective profits under oligopolistic competition. Among many ways, such coordination can for example come in the form of price-fixing schemes, in which two firms competing in the same market agree to fix product market prices at a higher than competitive level, or market allocation, in which competing firms agree to each serve a separate product category, geographic area, or demographic group.

Although the benefits might be substantial to the shareholders of participating firms, successful coordination is hard to achieve for several reasons. First, explicit collusion is illegal and suspected colluding firms might face legal actions (Department of Justice and Federal Trade Commission, 2000). Second, a tacit coordination equilibrium might be challenging to sustain, as it can be optimal for the participating firms to deviate by engaging in predatory behaviors, such as cutting prices or entering into their competitor's market segment (Wiseman, 2017). Third, communication channels among competing firms might be imperfect, so crucial competition-sensitive information such as distribution, marketing, and pricing schemes might not reach or be trusted by the rival decision-makers (Kandori and Matsushima, 1998; Genesove and Mullin, 2001; Awaya and Krishna, 2016).

We argue that board connections are one way to facilitate anti-competitive practices by alleviating the aforementioned hurdles. Board connections might give opportunities for direct communication between the competing firms about their product market strategies or labor and supply chain policies. Moreover, the professional and personal interactions between directors in competing firms can help build affinity and trust and make deviations from coordination less likely to occur. In this sense, board connections can be considered as a kind of relational contract as in Baker et al. (2002), in which the exchange of sensitive information is even unnecessary for competition to be hindered. Also, even the interactions among directors of competing firms on the boards of other unrelated firms could facilitate coordination. Observing the rival firms' director voting behavior on third boards could improve understanding of how decisions in the rival firms are made, which could then be internalized into more informed reaction functions for firms' strategic interactions. Directors might also become better aware of other firms' financial policies, and influence them to be less aggressive, in turn making the strategic competition less fierce.

The Clayton Act bans interlocking directorships if the competitive sales are more than $4,525,700, more than 2% of total sales for both firms, *and* more than 4% of total sales for either firm, where competitive sales are defined as the gross revenues for all products and services sold by one firm in competition with the other firm (Federal Trade Commission, 2023b). In reality, regulators rarely proactively searched for violations and over the past several decades its enforcement has been limited to the cases of merger reviews.[1] Moreover, it is the burden of regulators to consider whether two firms share the same product market and can be perceived to be competing. Competitive sales are usually analyzed and determined on a case-by-case basis by industry experts. In today's overlapping product markets, product market definition is often under debate.[2] We hypothesize that due to such constraints on

[1]More recently, the Department of Justice (DOJ) administered a series of investigations on director interlocks. On October 19, 2022, the DOJ shared that seven directors resigned from corporate board positions in response to concerns by the Antitrust Division that their roles violated the Clayton Act, followed by the resignation of five more directors on March 9, 2023 (Department of Justice, 2022, 2023). The FTC also raised its *first case in 40 years* that enforces Section 8 of the Clayton Act by barring interlocking directorship between two energy companies (Federal Trade Commission, 2023a).

[2]As an example, in its response to the inquiry of the United Kingdom's Competition Market Authority, Facebook said that it saw its market share as the "time captured by Facebook as a percentage of total user time spent on the Internet, including social media, dating, news, and search platforms". Similarly, Amazon (2020) reported that it "accounts for less than 1% of the $25 trillion global retail market and less than

enforcement many board connections between product market peers can be anti-competitive.

2 Board Connections and Firm Profitability

2.1 Data

In our large sample analysis on the prevalence of board connections and firm profitability, we draw our data from three sources: Compustat, BoardEx, and the 10-K Text-based Network Industry Classifications (TNIC) in the Hoberg-Phillips Data Library. We construct the sample from the set of firms in the intersection of Compustat and BoardEx and put the following restrictions: (1) the firm is not in the financial industry or the utilities industry (SIC between 6000 and 6999, or between 4900 and 4999); (2) the firm-year has inflation-adjusted total assets above \$10 million and sales above \$4 million in 2018 dollars; (3) the gross margin and operating margin for the firm-year are both above -50%.

To construct the network of directors, we use the BoardEx Individual Profile Employment Dataset and require the type of employment to be a board position. From this, we construct annual network snapshots, with the nodes as the firms and the edges as the pairwise direct connections (director interlocks). We then find board connections between firms that are product market peers based on the Hoberg-Phillips classification, which is calibrated to be as fine as the SIC-3 industries (Hoberg and Phillips, 2010, 2016). In particular, firm's competitors are determined by calculating the textual similarity scores of the firm's 10-K product descriptions with other firms and retaining those to which the score is above a certain threshold.

We define our main variables as follows. Gross margin is the ratio of gross profit to sales, operating margin is the ratio of operating income before depreciation and amortization to sales, ROA is the ratio of operating income before depreciation and amortization to total assets, assets is the natural logarithm of the firm's total assets in millions of dollars, sales growth is the percentage change of sales relative to the prior year, and Tobin's Q is the ratio

4% of retail in the US", suggesting that it defines its relevant market as not only online but also offline retail markets. In fact, when the Antitrust Subcommittee of the U.S. House of Representatives requested Amazon for a list its top competitors, Amazon identified 1,700 companies, including "a discount surgical supply distributor and a beef jerky company".

of the market value of equity plus book value of debt over total assets. Internet Appendix Table A1 tabulates the definitions of all variables we use in our analysis. All financial and accounting variables are winsorized at the 1% and 99% percentiles.

2.2 Sample description

We conduct a stacked difference-in-differences analysis of instances when a firm forms a new board connection to a product market peer. We study both direct and indirect board connections between product market peers. We define that two firms have a *direct* board connection if they share a director, and we define that two firms have an *indirect* board connection if they do not share any board members but a member of their respective boards serves on the board of the same intermediate firm. We expect that forming a new direct board connection to a product market peer has a stronger effect on firm profitability than forming an indirect one, but we also posit and later show in Section 3.1, that direct and indirect board connections might have different mechanisms for raising firm profitability.

Our "treated" firms consist of all firms that form a new direct or indirect board connection with a product market peer during the period 1999-2018. When identifying these instances of newly formed board connections, we ensure that the firm does not have any pre-existing direct or indirect board connection with its newly connected peers. We further ensure that, in the instances of forming an indirect connection, the firm does not concurrently form a direct connection with any of its peers.

We study how firm profitability changes following the formation of such connections. To control for general industry trends in the outcome variables, we match each treated firm to a control firm that is from the same industry and has similar firm characteristics in the year before treatment. More specifically, for each treated firm, we look for one control firm, and we match with replacement. The matching takes the following steps. First, following Fracassi and Tate (2012), we require that the control firm is in the same Fama-French 17 industry as the treated firm, and the control firm itself is not treated in the event year. Second, we look for candidate control firms in the same quantiles of assets, gross margin, and Tobin's Q and rank them by their Mahalanobis distance to the treated firm based on these three characteristics in the year prior to the treatment. Finally, we retain the one candidate control firm with the smallest Mahalanobis distance to the treated firm. That forms each cohort of treated and control firms. Our final sample comprises of a stacked set of these cohorts of treated and control firms for the treatment year, the three-year period before, and the three-year period after treatment, i.e., from year -3 to year +3 where year 0 refers to the treatment year.

Our sample consists of 1,493 events of new direct connections to product market peers, and 4,085 events of new indirect connections to product market peers via an intermediate firm.[3] [4] Table 1 reports the distribution of the treated firms' Fama-French 48 industries. The five industries with the most newly formed connections are Business Services (accounting for 20.6% of all events), Electronic Equipment (13.0%), Pharmaceutical Products (12.3%), Medical Equipment (8.5%), and Computers (7.7%).

Table 2 reports the summary statistics for the treated and control firms in the year prior to the treatment (i.e., the year for which firm characteristics are used in the matching procedure) and also for all firms in Compustat. Board connections to peers tend to occur in firms that are larger, have higher gross margin and Tobin's Q, and faster sales growth. Consistent with Geng et al. (2023), such connections are also more likely among research and development (R&D) intensive firms. The operating margin in treated firms, however, is lower than average as these firms also have higher selling, general, and administrative (SG&A) expenses. This table also shows that the treated and control firms are balanced in terms of the variables used in matching. In the tests reported in Section 4.3, we expand the set of matching co-variates and find the baseline estimates to be robust.

We also compare how directors involved in these new connections differ from an average director in the treated firms. Internet Appendix Table A2 shows that, while those connecting directors cross-sit on more boards and are more likely to be non-executive directors, their professional experience and educational level do not differ from that of an average director.

[3]Unconditional on being product market peers, board connections are quite prevalent in our sample. Over our sample period, we observe 57,809 new board connections formed between product and non-product market peers, of which 56.8% involve direct connections. A firm is on average directly connected to 4.4 firms and indirectly connected to 25.0 firms. In Section 4.1, we show that connections to a non-peer firm are not associated with increases in profitability.

[4]Internet Appendix Figure A1 shows that new board connections are spread out through our sample period. 51.8% (69.1%) of the new direct (indirect) connections last for less than 4 years, 38.0% (27.1%) last for 4 to 8 years, while 10.2% (3.8%) last for longer than 8 years.

2.3 Main findings

We study the impact of new board connections to product market peers on firm performance. To do this, we estimate a difference-in-differences model on our sample of treated and control firms. Our methodology of pooling observations of cohorts of treated and control firms together and estimating a difference-in-differences model follows Gormley and Matsa (2011), Gormley and Matsa (2016), and Gormley et al. (2023). The first difference is taken between the time period before and after the event while the second difference is between the treated and control firms. Our empirical model is then:

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}, \end{aligned} \tag{1}$$

where i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. $Y_{i,j,c,t}$ is one of our outcome variables: gross margin, operating margin, ROA, and sales growth. $Post_{c,t}$ is a dummy variable that takes the value of one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year.[5] $DirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms that experience a direct board connection to a product market peer while $IndirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms that experience a new indirect board connection to a product market peer. We include two sets of fixed effects: firm times cohort fixed effects $\theta_{i,c}$ and industry times calendar year fixed effects $\theta_{j,t}$ where industries are defined based on the Fama-French 48-industry classification. The latter control for wider industry-specific shocks. $DirectTreated_{i,c}$ and $IndirectTreated_{i,c}$ are left out of the regression as they are absorbed by the firm times cohort fixed effects. The coefficients of interest are β_1 and β_2 that identify the change in the outcome variable for treated firms that respectively form a direct and an indirect board connection with a product market peer. We cluster standard errors at the firm level to address serial correlation within a firm (Bertrand et al., 2004).

[5] $Post_{c,t}$ is not absorbed by industry times calendar year fixed effects because treatments occur in different years for different cohorts.

Table 3 reports the findings from estimating the above regression. Columns (1)-(3) show that profitability uniformly increases in the three years after the firm forms a new board connection with its product market peer. Also, the increase in profitability is greater following a direct connection as compared to that following an indirect connection, albeit the differences are weak in terms of the statistical significance.

Our estimates are economically meaningful. Column (1) suggests that the gross margin increases by 0.8 p.p. for a firm that forms a direct board connection with a product market peer. This is a 1.6% of the mean gross margin of the treated firms in the pre-treatment year. As reported in columns (2)-(3), our estimates of the increase in operating margin and ROA for a firm that forms a direct connection are 1.4 p.p. and 0.9 p.p., which constitute a much larger 11% and 10% of their respective mean values in the pre-treatment year.[6]

Consistent with firms limiting the expansion of their output while increasing their profitability following new board connections to their product market peers, in column (4), we report that the sales growth decreases by 2.5 p.p. after a firm forms a new direct connection with a product market peer. That said, we find no statistically significant effect on sales growth after a firm forms an indirect connection with a product market peer. In Internet Appendix Table A3, we report the findings for some other outcome variables. Consistent with firms gaining market power, we find that the sales increase at a faster pace relative to the cost of goods sold and also see an increase in markups calculated following Ayyagari et al. (2023). However, we find no evidence of reduced SG&A costs or increase in capital expenditure or R&D. If anything, we see a small drop in the size of total assets.

We next document the dynamics of the change in performance around new board connections. We estimate a dynamic version of regression (1) with the year prior to the event as the baseline year. We plot the coefficient estimates in Figure 1. Panels A1 and A2 report that there is no statistically significant difference in the gross margin between the treated and control firms in the years prior to the treatment. This suggests the absence of pre-existing trends. Panel A1, which reports the results for the direct connections, shows that the gross

[6] Gross margin is $\frac{\text{Sales-COGS}}{\text{Sales}} = 1 - \frac{\text{COGS}}{\text{Sales}}$ and operating margin is $\frac{\text{Sales-COGS-SG\&A}}{\text{Sales}} = 1 - \frac{\text{COGS}}{\text{Sales}} - \frac{\text{SG\&A}}{\text{Sales}}$, where COGS refers to costs of goods sold. Hence, due to an operating leverage effect, we would expect the increase in operating margin to be larger compared to gross margin if firms are gaining more pricing power and thus the sales expand at a faster rate than COGS and SG&A expenses, which is consistent with findings we later report in Internet Appendix Table A3.

margin of treated firms increases significantly starting from the second year following the formation of a new connection. Furthermore, the magnitude of the increase gets larger in the third year. This is consistent with the new director taking time to understand the board dynamics and the potential for coordination. Panel A2 reports the results for the indirect connections, showing a similar pattern, albeit smaller in the magnitude. We also find similar patterns for operating margin and ROA, as reported in Panels B1-2 and C1-2.

2.4 Endogeneity concerns

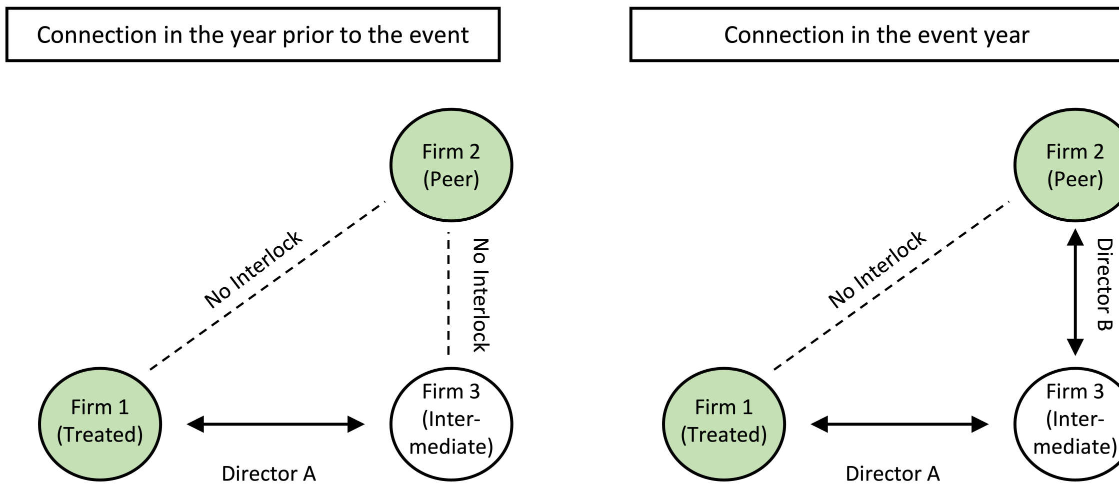
New board connections are by design endogenous to firm current and expected operating performance. For example, better-performing firms could afford appointing directors who are experts in their industry and thus also connected to product market peers. Also, the directors of a firm for which prospects are improving may be more valued in the director labor market and thus more likely to be appointed to the board of a product market peer. To circumvent these concerns, we now focus on newly built connections that are unrelated to focal firm's appointment actions.

2.4.1 Non-focal-firm initiated board connections

We note that new board connections to a product market peer can arise either from changes to a firm's board or from changes to the board of a connected firm. Hence, in the first test, we focus on new connections that are not formed because of changes in the focal (i.e., treated) firm's board, nor changes in other appointments of the focal firm's directors. That is, we look at the connections that are formed because of changes to a non-focal firm's board and thus are less likely to be correlated with the future prospects of the focal firm.

In particular, we focus on indirect connections and look at those connections to product market peers that are initiated due to changes in the boards of either the intermediate firm or the product market peer. We condition on the cases when the focal firm is already interlocked with the intermediate firm prior to the event year. In the event year, the board changes in either the intermediate firm or the product market peer. That is, either (1) the intermediate firm appoints a new director who is also on the board of a product market peer

Graph 1: Illustration of non-focal-firm initiated board connections



Note: This graph illustrates an example of the non-focal-firm initiated board connection changes. Firm 1 is the treated firm, i.e., the focal firm, and firm 2 is its product market peer. Firm 3 is the intermediate firm. We provide further details in Internet Appendix IA.2.

of the focal firm, or (2) a product market peer appoints a director who is also on the board of the intermediate firm. Consequently, the focal firm forms a new indirect connection to a product market peer via the intermediate firm but such new connection between the focal firm and its peer is not due to any changes to the board composition of the focal firm.

Graph 1 illustrates an example, where Firm 1 is the focal firm and Firm 2 is a product market peer of Firm 1. In the year prior to the event, Firm 1 and an intermediate firm, Firm 3, are interlocked through Director A who serves on the boards of both firms. Firm 1 does not have any direct or indirect connection to Firm 2. In the event year, Firm 2 becomes interlocked with Firm 3 via Director B. This can be either due to Firm 2 newly appointing Director B, who is also on the board of Firm 3, or due to Director B, who has always been on the board of Firm 2, additionally taking on a board position in Firm 3. Either way, Firm 1 now has an indirect connection with Firm 2, and this new connection is purely a result of changes in the composition of the board of directors of either the intermediate firm or a product market peer. It is not due to any change in the composition of Firm 1's board or due to changes in the directorships of any of its directors.

We construct a sample using only such focal firms, i.e., Firm 1 in Graph 1, as the treated firms and using the same definition of control firms as we used in difference-in-differences model (1). Out of the 4,085 events of indirect board connections in our overall sample, we find that 2,114 are initiated due to changes on the board of a firm other than the treated firm. Using only such connections, we present the findings in Panel A of Table 4. Consistent with our prior findings, column (1) shows that the gross margin of the treated firm increases by 0.7 p.p. in the three years following the initiation of a non-focal-firm initiated indirect board connection to a product market peer. This estimate is larger than our baseline estimates based on all indirect board connections that showed a 0.4 p.p. increase in the gross margin, and suggests that, if anything, those board appointments that might be considered as more likely to be caused by the prospects of the treated firm appear to bias our baseline estimates downwards. Columns (2) and (3) imply that consistent with our baseline estimates our findings are not sensitive to how we measure firm profitability.

The effects are economically significant. The increase in gross margin, operating margin, and ROA are 1.4%, 7.7%, and 10% of the mean values for the treated firms in the year before treatment, respectively. Figure 2 presents the corresponding findings in a dynamic model. Across the measures of profitability there is no pre-existing difference between the treated and control firms. We also show that profitability significantly increases in the three years following the initiation of such new indirect board connections.

While in these tests reported in Panel A of Table 4 the new indirect board connections of the treated firms are not due to any changes on their own boards, the intermediate firm could still be fundamentally similar with the treated firm. Hence, certain unobservable factors might drive both board changes in the intermediate firm and also the future performance of the treated firm. This could be a particular concern if the treated and the intermediate firms are product market peers themselves. Indeed, the intermediate firm is a Hoberg-Phillips peer of the treated firm in 752 non-focal-firm initiated new indirect board connections out of 2,114 in total. In Panel B of Table 4, we re-estimate the difference-in-differences regressions excluding cases where the intermediate firm is a product market peer of the treated firm and find similar estimates.

2.4.2 Merger-induced indirect board connections

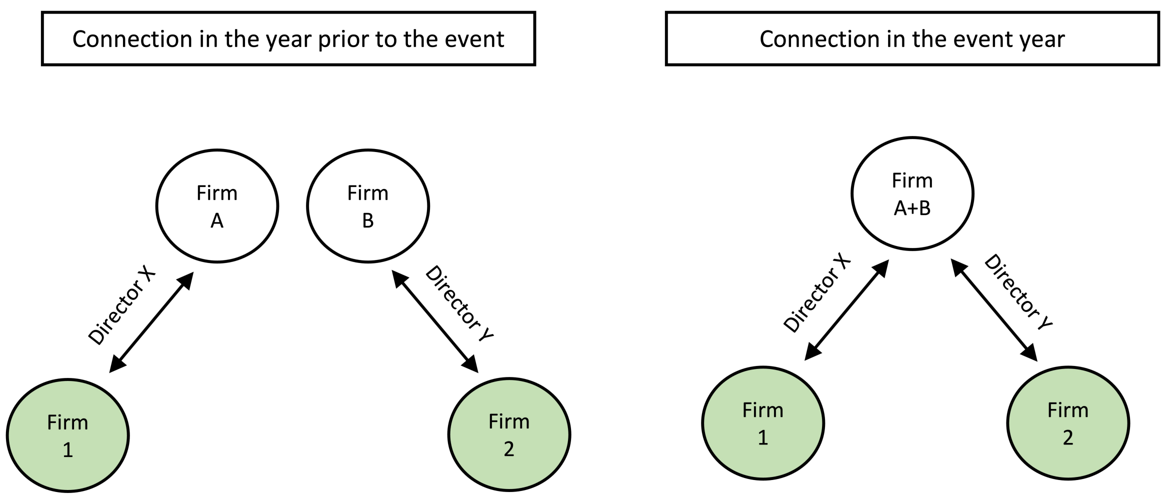
We further focus on a even smaller sample of firms to abstract from the remaining concerns that certain unobservable future prospects of both the peer firm and the treated firm affect the creation of the connection between the peer firm and the intermediate firm. We look at the indirect connections induced by the merger activity of the intermediate firm.

Consider the situation where Firm 1 shares a director with Firm A, Firm 2 shares a director with Firm B, and Firm 1 and Firm 2 are product market peers. When Firm A and Firm B engage in a merger, it is possible that the merged firm has directors from both merging firms, and as a result now the merged firm might share directors with both Firm 1 and Firm 2, giving rise to an indirect connection between Firm 1 and Firm 2. In these cases, treated firms, i.e., Firm 1 and Firm 2, do not experience mergers themselves. Graph 2 illustrates such situation by showing connectedness before and after the merger. Becher et al. (2019) show that acquiror directors often and target directors sometimes remain in the combined firm after the merger. In our case, we find 60 instances of merger-induced new indirect connections.

Internet Appendix Table A4 reports the estimated effects of such connections and Internet Appendix Figure A2 reports the dynamics. We find that after a firm experiences merger-induced indirect board connections, its gross margin, operating margin, and ROA rise by 0.2 p.p., 3.1 p.p. and 2.8 p.p., respectively. Despite the small sample size, the increase is statistically significant for operating margin and ROA. Becher et al. (2019) find that directors who remain on the board after mergers, especially those from the target firm, are a highly selected group that more often have experiences of mergers or serving as a CEO. Director appointment during normal times, instead, occurs for more routine reasons such as diversity, financial expertise, and retirement. It is possible that certain characteristics of the connecting directors in these merger-induced indirect connections are also conducive to easier coordination, which might explain higher estimates compared to the baseline findings.

Finally, one concern could be that we might be capturing the direct product market spillover effects that a merger between Firms A and B has on Firms 1 and 2 (Eckbo, 1983). In Panel B we alter the matching procedure and require that the control firm has a director

Graph 2: Illustration of merger-induced indirect board connections



Note: This graph illustrates an example of the merger-induced indirect board connection changes we discuss in Section 2.4.2. Firm 1 and Firm 2 are product market peers. Firm A and Firm B engage in a merger. Director X cross-sits on Firm 1 and Firm A and stays on the board of the combined firm after the merger. Director Y cross-sits on Firm 2 and Firm B and stays on the board of the combined firm after the merger.

who cross-sits on the board of a firm experiencing a merger as well, but such merger does not lead to new board connections of the control firm to its product market peers. That is, both treated and control firms have directors in firms experiencing mergers. We show that the findings remain similar, and gross margin, operating margin, and ROA rise by 0.9 p.p., 3.4 p.p. and 2.5 p.p., respectively.

Overall, we find evidence of increased profitability in cases where the new board connections are less likely to be correlated with unobservable focal firm future prospects.

3 Board Connections and Product Market Actions

Our findings are consistent with the interpretation that board connections to product market peers facilitate product market coordination among competing firms. That being said, board connections can also improve firm profitability without anti-competitive coordination. For instance, Bouwman (2011) shows that good corporate governance practices can propagate across firms via the network of directors. The newly appointed board members might also have connections to regulators and thus be in high demand among industry peers (Emery and Faccio, 2023). If board connections facilitate the spread of corporate governance practices that enhance a firm's internal efficiency or new directors otherwise benefit the firms with their industry experience, they can have positive effects on firm profitability without any anti-competitive concerns.

To establish that board connections are related to product market coordination, we first look for direct evidence using barcode-level data in the consumer goods sector. Second, we link the board network connections to the convicted collusion cases. Third, we examine a range of cross-sectional heterogeneities in the baseline effects on profitability.

3.1 Barcode-level prices and quantities

To corroborate the interpretation that our findings on profitability increase entails an anti-competitive mechanism, we provide direct evidence on how board connections affect competition outcomes based on barcode-level data. We rely on Nielsen Retail Scanner Data, which contain prices and quantities from retail chains across the US. Prior research has used this data to study the product market impacts of private equity (Fracassi et al., 2022), credit market disruption (Granja and Moreira, 2022; Kabir, 2022), common ownership (Aslan, 2023), and taxation (Baker et al., 2023). We extract prices and quantities at the weekly frequency and at a level as fine as each store and each Universal Product Code (UPC), which is a 12-digit barcode that identifies a unique traded item.

This granular data allows us to quantify firm's actual pricing and product placement decisions. We can also sharpen the definition of product market competitors. Product data are organized in a hierarchical structure, with around 125 "product groups" and 1,100 "product modules". For example, the "product group" labelled as "Cheese" has 19 "product modules", which include "Cheese-Natural-Mozzarella","Cheese-Natural-American Colby", and "Cheese-Natural-American Cheddar". We define peers as firms that sell in the same "product module" or "product group". We adopt a similar difference-in-differences framework as in the prior section and look at how prices of products and the tendency for market allocation change after firms form board connections to product market peers.

3.1.1 Sample construction and methodology

We start from the universe of Nielsen Retail Scanner Data in 2006-2020, which contain 6,087,712 distinct UPCs and record total annual sales of $260.7 billion on average. We start by matching each UPC to a producer based on the UPC prefix data provided in the GS1 Company Database. We are able to assign producer information to 77.1% of all UPCs. Next, we match producers in GS1 Company Database to firms in BoardEx based on their name strings. We are able to match producers of 2,715,025 UPCs to BoardEx, which account for 44.6% of all UPCs and 63.4% of the total sales in the Nielsen Retail Scanner Data. The details of the matching procedure are provided in Internet Appendix IA.4.

The relevant changes in board connections are defined in the same manner as in Section 2. Differently from our prior tests for which treated firms have to be publicly listed and thus have financial information, in this analysis treated firms can be either publicly listed or privately held. Also, as we have outcomes at a higher frequency, we define board connection events at the quarterly level. We build the relationship network based on all firm personnel and require the person connecting product market peers to be a director in at least one side of the connected firm-pair. When using a "product module" as the product category, which is the finest level in the data, we find 52 pairs of product market peers that form new direct board connections and 778 that form indirect ones. Using the higher level aggregation of a "product group" and thus a larger size of each "industry", we instead find 74 pairs that form new direct board connections and 1,067 that form indirect ones. We provide findings under both classifications.

We construct three groups of outcome variables that respectively capture the price, quantity, and firm-pairs' tendency to compete head-on. First, we construct a price index following Aslan (2023). We define the set of products (UPCs) that firm i sells in product category c and 3-digit zip code area z and quarter t as its product portfolio and denote it as $U_{i,c,z,t}$. The share of revenue of each product u within the product portfolio is $w_{u,z,t}$, which sums up to one for a product portfolio, that is, $\Sigma_{u \in U_{i,c,z,t}} w_{u,z,t} = 1$. We define the average dollar price of product u in area z in quarter t to be $p_{u,z,t}$. The price index $P_{i,c,z,t}$ of firm i in product category c and area z and quarter t is then:

$$P_{i,c,z,t} = \Sigma_{u \in U_{i,c,z,t-1}} \, w_{u,z,t-1} \times (p_{u,z,t}/p_{u,z,t-1} - 1). \tag{2}$$

$P_{i,c,z,t}$ thus reflects the weighted average of firm i's UPC price changes in a category c in area z in quarter t, weighted by the firm i's UPC shares in category c. We exclude a UPC if the unit price in the current quarter is below 33% or above 300% of the prior quarter. We also exclude an observation $P_{i,c,z,t}$ if the total sales are below \$5,000 (\$10,000) or the market share is below 5% (1%) for firm i in product module (group) c and area z in the current quarter t or the prior quarter $t-1$.

Second, to capture the quantity effects of board connections, we construct a quantity index. We denote the number of units of product u sold in area z in quarter t to be $q_{u,z,t}$. Similar to the price index, the quantity index $Q_{i,c,z,t}$ of firm i in product category c, area z, and quarter t is:

$$Q_{i,c,z,t} = \Sigma_{u \in U_{i,c,z,t-1}} \, w_{u,z,t-1} \times (q_{u,z,t}/q_{u,z,t-1} - 1). \tag{3}$$

Both $P_{i,c,z,t}$ and $Q_{i,c,z,t}$ are winsorized at the 1% and 99% percentiles.

Third, we obtain the firm-pair-level cosine similarity of the geographic distribution of sales. That is, compared to price and quantity indices, we aggregate observations across geographic areas to firm-pair i and j and quarter t level. We restrict to pairs of firms that sell in the same product module and have quarterly sales above \$100,000. We represent a firm i's share of sales in each 3-digit zip code area in quarter t as a vector $v_{i,t}$ and calculate the cosine similarity for each firm-pair i and j:

$$s_{i,j,t} = \frac{v_{i,t} \cdot v_{j,t}}{\|v_{i,t}\| \|v_{j,t}\|}. \tag{4}$$

We keep all observations of untreated firms and the observations of all treated firms in a $[-6, 8]$ time window around the treatment, where quarter 0 is the quarter in which new board connections are formed. The $Treated \times Post$ variable equals one for treated units in the quarters post treatment and zero otherwise.

3.1.2 Product prices and quantities

Compared to the tests for profitability effects discussed in Section 2, we sharpen the treatment definition. In particular, we define new connections at the firm times product category times 3-digit zip code area level. That is, for each newly-connected firm-pair, we zoom into each 3-digit zip code area that both firms operate in and calculate the sum of their market shares within this area in the quarter right before the treatment. If their joint market share exceeds a threshold, we say that these two firms *in this area* are treated. By applying the threshold, we identify the actual product market overlap and rule out situations where two firms both operate in the same product category and the same geographic area but they have inconsequential market share in that area.

We then estimate the following tightly-specified difference-in-differences regression,

$$\begin{aligned} Y_{i,c,z,t} = {} & \alpha_1 \times DirectTreated_{i,c,z} \times Post_{i,c,z,t} + \alpha_2 \times IndirectTreated_{i,c,z} \times Post_{i,c,z,t} \\ & + \theta_{i,c,z} + \theta_{c,t} + \theta_{i,t} + \theta_{z,t} + e_{i,c,z,t}. \end{aligned} \tag{5}$$

We include firm times product category times area fixed effects $\theta_{i,c,z}$ so that we are capturing the differential trends in outcome variables between the treated units and the control units rather than their baseline differences. We also include product category times quarter fixed effects $\theta_{c,t}$ and firm times quarter fixed effects $\theta_{i,t}$ to partial out within-product-category and within-firm time trends. As the same firm can produce in many product categories, and the peer firm it forms a board connection with might produce in some but not all the same product categories, we can exploit variations within firm and time. In addition, we include area times quarter fixed effects $\theta_{z,t}$ to control for local economic dynamics that could correlate with the level of concentration in the local product markets and affect prices. We cluster the standard errors at the firm level.

We report our findings using "product module" as the product category in Table 5. In column (1), we use the price index as the outcome variable with a threshold of at least 10% on the joint market share of the treated firm and its newly connected peer in the local market. We find that in the quarters post direct board connections, the per-quarter increase in product price is 0.22 p.p. faster for treated firms in their product modules that are affected by direct board connections compared to the rest, which corresponds to a 0.88 p.p. annualized difference. For indirect connections, the effects are 0.07 p.p. per quarter, which is consistent with direct connections having a more prominent role at facilitating product market coordination than indirect connections. Both effects are statistically significant. In columns (2) and (3), we apply the thresholds of 5% and 3% on the market share in the local area. The magnitude of estimated treatment effects slightly decreases, which is consistent with a larger market share making coordination easier.

In columns (4)-(6), we use the quantity index as the outcome variable. We find that the quantity index is significantly lower for the firms in their product categories that are treated with board connections. Such quantity suppression is consistent with the higher prices and product market coordination.

We also repeat these tests based on "product group", which is a broader category, and report the findings in Internet Appendix Table A5. While this classification gives more firms in each product category and thus more instances of connections, the products are less similar and the definition of treatment is less precise. Consistent with this, we find that the magnitude of estimated treatment effects are smaller for both outcome variables.

In addition, we investigate the effects of board connections for non-focal-firm initiated changes which we describe in Section 2.4.1 and report our findings in Internet Appendix Table A6. We find that, similar to the findings in Section 2.4.1, approximately half of the new indirect connections fall into this criteria. The findings remain robust, suggesting that these board connections that are less likely to be correlated with firms' future prospects also have effects on product market outcomes.

3.1.3 Market allocation

The FTC deems agreements among competitors to divide sales territories or assign customers as "almost always illegal" based on the rationale that such arrangements are essentially agreements not to compete (Federal Trade Commission, 2022). For example, it uncovered and prosecuted an agreement when two chemical companies agreed that one would not sell in North America if the other would not sell in Japan (Federal Trade Commission, 2002). Prior research has also studied how firms could utilize tacit market allocation to profit (Sullivan, 2020; De Leverano, 2023). We formally test how the tendency for product market peers to compete head-on changes after board connections. We estimate the following model on the firm-pair i and j, and quarter t panel:

$$
\begin{aligned}
s_{i,j,t} = {} & \alpha_1 \times DirectTreated_{i,j} \times Post_{i,j,t} + \alpha_2 \times IndirectTreated_{i,j} \times Post_{i,j,t} \\
& + \theta_t + \theta_{i,j} + e_{i,j,t}
\end{aligned}
\tag{6}
$$

where i and j are indices for the firms i and j, t indexes the quarter, and $s_{i,j,t}$ is the cosine similarity score of the geographic distribution of the two firms' sales portfolios. We include firm-pair fixed effects $\theta_{i,j}$ and quarter fixed effects θ_t, and cluster standard errors at the firm-pair level.

We report our findings in Table 6. Column (1) shows that cosine similarity score falls by 0.0037 on average after firm-pairs form indirect board connections, which is 3.69% of the within-firm-pair standard deviation (0.1004). However, we do not observe a drop in the score following direct interlocks. Columns (2) and (3) further indicate that the results are robust to measuring similarity of firm-pairs' sales by county or by designated marketing area (DMA). These findings suggest that product market peers adjust their geographic distribution and tilt away from one another after the formation of board connections, which is consistent with board connections enabling deliberate market allocation to avoid head-on competition.

This evidence also enlightens us about the differential mechanisms underlying direct and indirect board connections. While direct connections have much stronger effects on product market prices than indirect connections, likely due to more difficult coordination, only indirect connections are related to the tendency for market allocation.

3.2 Convicted collusion cases

Do these new board connections also relate to the actual convicted collusion cases? We obtain data on convicted collusion cases from the Private International Cartels Database (Connor, 2020). We acknowledge the caveats of studying convicted cases, as only about 10% to 30% of all collusion conspiracies are detected (Connor, 2014), and those that are detected may not be the most economically important ones.

We restrict the sample to firms headquartered in the US and hand-match these firms to the universe of firms we described in Section 2.2. We then construct a firm-pair-year level indicator of whether two firms are in an active convicted collusion in a certain year. We also construct the degree of separation of each firm-pair in the network described in Section 2.2, which is the minimum number of intermediate nodes (i.e., firms) between two nodes that can connect them together. We exclude firm-pairs that are unconnected in the director network or connected but with a degree of separation above four.

In Internet Appendix Figure A3, we plot the probability of a firm-pair having an active convicted collusion, conditional on the degree of separation of these two firms in the director network. While a directly connected firm-pair (zero degree of separation) has a 0.058% probability of having an active convicted collusion and this probability is 0.061% for firm-pairs with one degree of separation, it becomes 0.017% for firm-pairs with two degrees of separation and 0.004% for firm-pairs with three degrees of separation. This strong associative relationship further suggests the director network's role in facilitating anti-competitive practices. We defer a detailed analysis of the convicted collusion to Internet Appendix IA.3.

3.3 Cross-sectional heterogeneities

We next perform five tests for cross-sectional heterogeneities in the profitability effects discussed in Section 2. We focus on scenarios where the anti-competitive effects are likely to be stronger. Specifically, we examine how the effects of board connections on profitability vary with: (1) exposure to Corporate Opportunity Waiver (COW); (2) whether the newly connected firm-pairs share common corporate customers; (3) the similarity in business descriptions of newly connected firm-pairs; (4) the Herfindahl–Hirschman Index (HHI) of the treated firm's industry; (5) the returns to scale of the treated firm's industry.

To test our predictions, we estimate the following triple-difference model:

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_4 \times Post_{c,t} \times EventCharacteristic_c \\
&+ \beta_1 \times Treated_{i,c} \times Post_{c,t} + +\beta_2 \times EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t} \\
&+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}, \qquad (7)
\end{aligned}
$$

where $EventCharacteristic_c$ is a sorting variable in the cross-section. It equals one for the time series of both the treated firm and its control if the new connections are exposed to COWs, share common corporate customers, or are in the top or bottom half in terms of a certain other characteristic. For brevity, we pool events of new direct and indirect connections together into $Treated_{i,c}$. $Treated_{i,c}$, $EventCharacteristic_c$, and $EventCharacteristic_c \times Treated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. We only report the coefficients on the double-difference terms and the triple-difference terms.

3.3.1 By exposure to Corporate Opportunity Waivers (COWs)

Before the staggered introduction of COWs in some states, directors were subject to corporate opportunity doctrine, which prohibits directors from pursuing outside corporate opportunities without first presenting them to the company on the board of which they serve. The introduction of COWs reduced the legal risk of sharing information outside the board. Geng et al. (2023) suggest that COW introduction led to an increase in the frequency of board overlaps. Following Eldar and Grennan (2023), we consider a firm to be subject to COWs in or after the year when the law was introduced in the firm's state of incorporation.

Internet Appendix Table A7 shows that board connections to product market peers are more frequent when the COWs are in effect. We find that firms are 2.3 p.p. more likely to form new board connections to product market peers when COWs are in effect, which is a 25% increase relative to the unconditional mean of 9.1 p.p. We further study whether previously estimated profitability effects of board connections are larger when COWs are in place. Indeed, Panel A of Table 7 shows that effects of board connections are concentrated in firm-years when COWs become effected. This evidence suggests that legal changes in recent decades might have exacerbated both the formation and anti-competitive effects of board connections.

3.3.2 By whether the newly connected firm-pairs share corporate customers

We expect the coordination benefits to be stronger when two firms share major corporate customers. To identify customer-supplier relationships in the network, we rely on firms' self-reported major customers from the WRDS Supply Chain Dataset, the construction of which is detailed in Cen et al. (2016), Cen et al. (2017), and Cohen and Frazzini (2008). We find that out of all events, 383 are between firm-pairs that share a major customer. Panel B of Table 7 reports estimates from our triple-difference regressions. In the case of operating margin, we find that the effects are stronger when firms share major customers. While it rises by 0.9 p.p. when newly connected firm-pairs do not share major customers, the change becomes 2.7 p.p. when they do.

3.3.3 By similarity in the business descriptions between connected firm-pairs

We next sort the new board connections based on the cosine similarity scores of business descriptions between the connected firm-pairs. We define a dummy variable, $TopSimilarity$, which equals one for the treated and control firms involved in events in which the connected firm-pairs have a cosine similarity score above the sample median and additionally are in the same SIC-3 industry. Panel C of Table 7 reports estimates from our triple-difference regressions. The triple-difference terms are positive and statistically significant for operating margin and ROA. New board connections lead to a 0.2 p.p. (0.6 p.p.; 0.5 p.p.) increase in gross margin (operating margin; ROA) for board connections where $TopSimilarity$ is equal to zero, and these effects become 1.0 p.p. (1.9 p.p.; 1.4 p.p.) when $TopSimilarity$ is equal to one. This provides evidence that the effects of new board connections are stronger between firm-pairs with more similar business descriptions and presumably operating closer in the product space. Importantly, this finding also attenuates the concern that the Hoberg-Phillips classification fails to capture the extent of product market rivalry.

3.3.4 By HHI of the treated firm's industry

Firms in more concentrated industries could find it easier to coordinate product market actions (Motta, 2004; Huck et al., 2004). To test if the effects are stronger in more concentrated industries, we sort firms based on the HHI provided in Hoberg and Phillips (2016) and define $TopHHI$ to equal one if the firm is in the top half in terms of its industry's HHI. Panel D of Table 7 reports estimates from triple-difference regressions. We see that the effects are indeed stronger in more concentrated industries, but the differential effects are not statistically significant. One potential reason for the lack of significance could be that firms in more concentrated industries might have alternative effective mechanisms to coordinate their actions. We also recognize that the HHI estimated based on the data of publicly listed firms might not reflect the actual degree of industry concentration (Ali et al., 2008). Possibly, this could also mean that the overall degree of industry concentration is not a necessary condition to take advantage of product market peer board connections.

3.3.5 By returns to scale of the treated firm's industry

As an alternative to the HHI based on publicly listed firms, we use the returns to scale in an industry as a proxy for the extent of competition. An industry is more likely to be oligopolistic if it exhibits increasing returns to scale. Following Dong et al. (2019), we estimate a two-factor Cobb-Douglas production function for each industry using data of the year 1999. We describe the procedure in greater details in Internet Appendix Table A1. We classify the firms according to whether their industry is experiencing above median returns to scale and estimate triple-difference regressions. As reported in Panel E of Table 7, the effects of new board connections are stronger in industries that exhibit greater increasing returns to scale – forming new board connections is followed by an increase in gross margin (operating margin; ROA) of 0.7 p.p. (1.4 p.p.; 1.0 p.p.) in industries with top half $ReturnstoScale$, while the increase is 0.4 p.p. (0.6 p.p.; 0.5 p.p.) in industries with bottom half $ReturnstoScale$.

4 Robustness Tests

In this section, we conduct a range of robustness tests. First, we confirm the robustness of our findings to controlling for customer-supplier relationships, joint ventures and strategic alliances, as well as common ownership. Next, we show our findings to be robust to alternative commonly used industry classifications but not robust to pseudo industry clasifications using non-product market peers. We then show that our findings are robust to alternative choices in the matching procedure and the regression specifications.

4.1 Controlling for confounding firm relationships

4.1.1 Customer-supplier relationships

One might argue that a firm and its suppliers can also have similar languages in their business descriptions and the Hoberg-Phillips industry classification might capture such relationships. Board connections between such firms may have positive effects on a firm's profitability for reasons outside of the scope of product market coordination. To address this concern, we check if any of the new board connections we identify are between customer and supplier firms. We find that out of all new board connections in Section 2.2, 68 are between pairs of customer-supplier firms based on the WRDS Supply Chain Dataset. As reported in Panel A of Table 8, our main findings are very similar if we focus on board connections between firms that are not customer-supplier pairs.

4.1.2 Joint ventures and strategic alliances

We also investigate the possibility that the profitability increase comes from the formation of joint ventures or strategic alliances that are associated with new shared board connections to solidify the relationships. Using the Securities Data Company (SDC) Database, we find that 213 new connections are between firms that ever started joint ventures or formed strategic alliance during our sample period. In Panel B of Table 8, we show that baseline estimates are robust to controlling for such relationships. This makes us more confident that we are not capturing effects of such explicit agreements among firms that antitrust authorities cleared to be benign and not anti-competitive in nature.

4.1.3 Common ownership

Further, recent research has studied the role of common ownership in anti-competitive conduct (Azar et al., 2018, 2022; He and Huang, 2017; Nain and Wang, 2018; Koch et al., 2021). One way how common ownership affects firm actions can be through shared board connections. An increase in common ownership between the treated firm and its product market peers can be accompanied by the establishment of new board connections. For example, an investor may appoint the same directors to its portfolio firms in the same industry. Even when a common investor appoints different directors to different firms, these directors might still belong to the same network and be more likely than a random director to simultaneously serve on a third intermediate firm. Indeed, Azar (2022) showed a substantial overlap between firm common ownership and board interlock networks.

Noting this prior evidence, we further address the possibility that the profitability-enhancing effects of board connections that we discover purely stem from common ownership. We use the firm-pair level measures of common ownership developed in Gilje et al. (2020) (GGL_{linear}, GGL_{fitted}, and GGL_{full_attn}) and Amel-Zadeh et al. (2022) (kappa, κ). We estimate the double-difference regression (1) and additionally control for concurrent *changes* in within-industry common ownership $\Delta(CommonOwnership)_{i,c}$,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times Treated_{i,c} \times Post_{c,t} \\ &+ \gamma_1 \times \Delta(CommonOwnership)_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{8}$$

We construct $\Delta(CommonOwnership)_{i,c}$ in two ways, which are common ownership with all of a firm product market peers or with its newly connected product market peers. First, we calculate the mean of common ownership between a treated or control firm and all of its Hoberg-Phillips product market peers during [0, +3] minus the mean during [-3, -1]. It is a constant for each time series of seven years (from τ = -3 to +3). We then scale it by its sample standard deviation. We report the findings in Panels C-F in Table 8. We also calculate the post minus prior change in mean common ownership between a treated firm and its newly connected peers, which takes a value 0 for control firms. For these we report the findings in Panels G-I.

As κ is only available for single-class S&P 500 firms and we are able to construct within-industry average κ for 13.7% of all observations, the sample size is smaller in Panel C. We find that controlling for the dynamic effects of concurrent changes in within-industry common ownership, treated firms still experience significantly higher growth in profitability compared to control firms. The coefficient estimates are similar to our findings in Table 3. This suggests that the profitability-enhancing effects of board connections are not fully capturing effects of potential concurrent increases in within-industry common ownership and present a related but distinct phenomenon.

4.2 Robustness to alternative industry classifications

4.2.1 Commonly used alternative industry classifications

In Internet Appendix Table A8, we further provide robustness to the definitions of industry peers. Instead of defining them according to the Hoberg-Phillips classification, Panel A uses the competitors disclosed by firms and recorded in FactSet Supply Chain Relationships (formerly, Revere) Database. Panel B instead defines industry peers based on the SIC-3 industry, while Panel C uses the SIC-4 industry. Further, Panels D and E use the GICS 6-digit and 8-digit industries. We find consistent evidence of an increase in profitability after firms form new industry peer board connections.

4.2.2 Pseudo industries

We further conduct a test in which, instead of actual product market peers, we study the effects of connections to non-product market peers, i.e., we use pseudo industry classifications. We construct the sample as follows. We start by generating a random group of firms that we designate as the "pseudo industry" for each firm-year. We use this pseudo industry in place of the Hoberg-Phillips industry to identify new board connections. We ensure that none of the firms in the pseudo industry are actually in the Hoberg-Phillips industry and keep the size of the pseudo industry to be the same as the Hoberg-Phillips industry. We exclude the pseudo events that coincide with connections to actual product market peers. Effectively, we study how firm connections to non-product market peers affect performance while keeping the sizes of the pool of firms similar between actual product market peers (Hoberg-Phillips industry) and non-product market peers (pseudo industry).

We then estimate the regression (1) and report the findings in Table A9. We do not find a statistically significant increase in profitability following the establishment of board connections to non-product market peers. That is, not all new board connections matter: the effects we document earlier do not come mechanically from any board connections but arise due to board connections to product market peers.

4.3 Robustness to alternative matching schemes

4.3.1 Use two or three matches instead of one

Our baseline tests use one control firm for each treated firm. We repeat the matching process with two or three control firms for each treated firm. The estimated effects of new board connections presented in Panels A and B of Internet Appendix Table A10 are virtually identical to those in Table 3.

4.3.2 Match on the number of new appointments during the event year

Treated firms appoint on average one new director during the event year, while control firms appoint an average of 0.64 directors. We next address the concern that the appointment of new directors to the board by itself might have positive effects on profitability. For instance, new directors might put extra effort at the beginning of their tenure, possibly due to career concerns. The pseudo industry tests reported in Section 4.2 partially address this concern. In those cases in Section 2.4.1 in which we study non-focal-firm initiated board connections, the pure new appointment effect is also not a concern. Still, in Panel C we refine the matching procedure and incrementally require that the treated firm and its control have exactly the same number of newly appointed directors during the event year. Our estimates are similar to those in Table 3.

4.3.3 Match additionally on other co-variates

Table 2 shows that treated and control firms are not statistically significantly different in terms of co-variates used in matching. Also, we do not see pre-trends in Figure 1, so any residual unbalancedness in firm characteristics is unlikely to be driving our main findings. Nevertheless, we now provide robustness tests where we modify the matching procedure.

In Panel D of Table A10, we examine the robustness using operating margin instead of gross margin in the matching scheme. We also sequentially add operating margin, sales growth, ROA, R&D to assets, and capital expenditures to assets to the matching scheme, and report the findings in Panels E, F, G, H, and I, respectively. We match on all variables in Panel J. Our findings under the new matching schemes remain robust.

4.3.4 Require that the control firm is never treated before or during [-3, 3]

In the matching process, we require that the control firm is not treated in the event year. Nonetheless, it is possible that it might be treated a few years before the event or right after. To avoid these cases affecting our estimates, we additionally require that the control firm is never treated during the [-3, 3] window around the event year in Panel K. In Panel L, we additionally require that the control firm is never treated both during or before the [-3, 3] window. Our findings are unaffected by these alternative choices. As we use stacked regression estimators and already-treated firms never act as effective control units in Panel L, our estimates stand to the critique in, e.g., Baker et al. (2022), on the interpretation of difference-in-differences estimates.

In addition, in Internet Appendix Table A11, we examine the cross-sectional heterogeneities in treatment effects as in Table 7 but under alternative matching schemes. We also show the dynamics of the difference in outcome variables between treated and control firms under alternative matching schemes in Appendix Figure A4. The patterns are similar to our findings under the baseline matching scheme.

4.4 Robustness to alternative regression specifications

We provide additional robustness tests with regard to the regression specifications. First, in Panel A of Internet Appendix Table A12, we estimate the effects of direct and indirect connections in separate regressions and obtain similar findings. Second, Panels B and C show that the estimates are robust to using alternative industry definitions such as SIC-3 and FIC-200 to define industry times year fixed effects. This gives us further confidence that our estimates are not capturing industry-level common trends. Finally, in our baseline tests, we cluster the standard errors at the firm level. It is possible that the outcome variables of connected firm-pairs are positively correlated and treating them as independent units could lead us to inflating the power of the tests. Hence, we define a new unit of clustering, which is all observations of a connected firm-pair for treated firms and all observations of a single firm for control firms. As shown in Panel D of Internet Appendix Table A12, while the T-stats drop slightly for some estimates, they all remain statistically significant.

5 Additional Evidence

Finally, we provide auxiliary evidence on the stock market reaction to connected director appointments, and the reverse reaction on profitability following connected director deaths. We also provide additional evidence on how the effects vary by director characteristics.

5.1 Stock market reaction to director appointments

In Table A16, we report the cumulative abnormal returns (CARs) in the days around the announcement of director appointments that trigger board connections to peers. We obtain the announcement dates from the Director and Officer Changes Dataset provided by Audit Analytics. We calculate the CARs using the market model and a seven-day window centered around the announcement dates and report the means in column (1). The average CAR after a firm announces the appointment of a director who cross-sits on the board of a product market peer is 0.83%. When a director cross-sits on an intermediate firm that is connected to a peer, the average CAR is 0.73%. In column (2), we report the CARs with the abnormal return calculated as the firm return minus the market return and find similar effects.

These announcement returns are statistically significant and are much larger than the CARs around the announcement of non-interlocking appointments as reported in the bottom row, suggesting that the market reacts positively to the appointments under study.

5.2 Connected director deaths

We next study instances of the deaths of interlocked directors. The death of a director breaks the relationship between the two firms. We find 51 such instances and construct a treatment-control matched sample as before. The results are reported in Internet Appendix Table A15. Despite the small sample, we find that the affected firm's gross margin (operating margin; ROA) drops by 1.8% (3.1%; 1.8%) following the death of the connected director. The double-difference terms are statistically significant for operating margin and ROA.

5.3 Director characterstistics and effects of board connections

We look at two director characteristics: whether they act as executives, and whether their appointments are inbound or outbound. First, based on the Non-Executive Director Indicator in BoardEx, we classify the new direct connections as involving executives if the director linking the newly connected firms is either an executive in the treated firm or an executive in its newly connected peer. Similarly, in the case of new indirect connections between product market peers Firm 1 and Firm 2 via an intermediate firm Firm 3, we classify the new connections to involve executives if Director X who connects Firm 1 and Firm 3 is an executive in Firm 1, or Director Y who connects Firm 2 and Firm 3 is an executive in Firm 2. We find that 395 out of 1,493 new direct connections involve an executive, and 1,199 out of 4,085 indirect connections do.

We pool the four kinds of events identified above together and estimate double-difference regressions. Internet Appendix Table A13 shows positive and mostly statistically significant effects when looking at events that only involve non-executive directors, suggesting that coordinating behavior is also present in the connections via non-executive board members. The effects of connections that involve executives are weakly stronger than those that only involve non-executive directors, which is consistent with competition-sensitive information being more likely to flow across firms when connected directors are also executives who are likely more engaged in firms' product market actions.

Furthermore, in Internet Appendix Table A14, we compare new appointments to the board of the treated firm, i.e., inbound directors, to the cases when existing directors in the treated firm are appointed to a peer firm, i.e., outbound directors. We find no consistent pattern in the differences between the effects. These findings are more consistent with an anti-competitive interpretation than with internal efficiency improvements, as the latter is more likely to be effectuated by newly appointed inbound directors.

6 Conclusion

Taking advantage of the networks formed by director interlocks and the Hoberg-Phillips industry classification, we find that board connections to product market peers have positive profitability implications. Specifically, a firm's gross margin rises by an average of 0.8 p.p. after forming new direct connections to product market peers and by 0.4 p.p. after forming new indirect connections to product market peers via an intermediate firm. We address endogeneity concerns by exploring the network structure and focusing on new connections that are less likely to be correlated with future firm prospects.

We remain agnostic over the specific strategy and form of anti-competitive practices that board connections facilitate between peer firms. Connected firms might engage in market allocation and target separate product categories, demographic groups, or geographic areas, and wield market power in their respective market segments. Alternatively, they might sell in the same market and fix the product prices at a higher level. The coordination can come via pure information exchange, or alternatively the social network could build trust and affinity among competing firms and make market allocation or price-fixing more sustainable. Using scanner data in the consumer goods sector, we do however find that such connections are associated with higher product prices and a greater tendency for market allocation.

This paper has several regulatory implications. First, our findings indicate the role of directors in anti-competitive practices and provide support for the current ban on interlocking directorships between competing firms. Our analysis of product market data shows that board connections are related to both product price increases and market allocation. Second, we find that indirect connections via an intermediate firm also have positive effects on firm profitability and product market actions, albeit their economic magnitudes are smaller than those of direct connections. This argues for going beyond director interlocks and putting restraints on indirect board connections between competitors as well, especially in cases where the detrimental effects of anti-competitive practices on consumer welfare are substantial.

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Table 1: Industry distribution of events

Fama-French industry	# Direct	%	# Indirect	%	# Total	%
Agriculture	1	0.1%	2	0.0%	3	0.1%
Food Products	2	0.1%	14	0.3%	16	0.3%
Candy & Soda	2	0.1%	3	0.1%	5	0.1%
Beer & Liquor	2	0.1%	5	0.1%	7	0.1%
Recreation	0	0.0%	1	0.0%	1	0.0%
Entertainment	10	0.7%	35	0.9%	45	0.8%
Printing & Publishing	4	0.3%	18	0.4%	22	0.4%
Consumer Goods	3	0.2%	6	0.1%	9	0.2%
Apparel	7	0.5%	22	0.5%	29	0.5%
Healthcare	55	3.7%	151	3.7%	206	3.7%
Medical Equipment	155	10.4%	317	7.8%	472	8.5%
Pharmaceutical Products	227	15.2%	460	11.3%	687	12.3%
Chemicals	6	0.4%	57	1.4%	63	1.1%
Rubber & Plastic Products	0	0.0%	2	0.0%	2	0.0%
Construction Materials	2	0.1%	20	0.5%	22	0.4%
Construction	5	0.3%	30	0.7%	35	0.6%
Steel Works Etc	2	0.1%	27	0.7%	29	0.5%
Machinery	51	3.4%	137	3.4%	188	3.4%
Electrical Equipment	6	0.4%	25	0.6%	31	0.6%
Automobiles & Trucks	2	0.1%	33	0.8%	35	0.6%
Aircraft	2	0.1%	26	0.6%	28	0.5%
Shipbuilding, Railroad Equipment	0	0.0%	9	0.2%	9	0.2%
Defense	0	0.0%	5	0.1%	5	0.1%
Non-Metallic & Industrial Metal Mining	3	0.2%	5	0.1%	8	0.1%
Coal	2	0.1%	6	0.1%	8	0.1%
Petroleum & Natural Gas	99	6.6%	326	8.0%	425	7.6%
Communication	0	0.0%	2	0.0%	2	0.0%
Personal Services	4	0.3%	38	0.9%	42	0.8%
Business Services	307	20.6%	840	20.6%	1,147	20.6%
Computers	109	7.3%	322	7.9%	431	7.7%
Electronic Equipment	214	14.3%	509	12.5%	723	13.0%
Measuring & Control Equipment	41	2.7%	145	3.5%	186	3.3%
Business Supplies	2	0.1%	17	0.4%	19	0.3%
Shipping Containers	0	0.0%	2	0.0%	2	0.0%
Wholesale	26	1.7%	92	2.3%	118	2.1%
Retail	95	6.4%	273	6.7%	368	6.6%
Restaraunts, Hotels, Motels	32	2.1%	68	1.7%	100	1.8%
Banking	2	0.1%	2	0.0%	4	0.1%
Insurance	0	0.0%	2	0.0%	2	0.0%
Trading	0	0.0%	4	0.1%	4	0.1%
Almost Nothing	13	0.9%	27	0.7%	40	0.7%
Total	1,493	100.0%	4,085	100.0%	5,578	100.0%

Note: This table reports the distribution of treated firms in the Fama-French 48-industry classification.

Table 2: Comparison of treated and matched control firms

	Treated			**Control**					**Compustat Sample**	
	Mean	SD	N	Mean	SD	N	Dif	T-stat	Mean	SD
Variables used in matching										
Assets	6.71	1.85	5,578	6.68	1.86	5,578	0.04	1.0	6.58	2.04
Gross Margin	0.51	0.26	5,578	0.51	0.24	5,578	0.00	0.9	0.42	0.24
Tobin's Q	2.67	2.03	5,578	2.62	1.88	5,578	0.06	1.6	1.82	1.40
Variables not used in matching										
Operating Margin	0.13	0.20	5,571	0.17	0.18	5,558	–0.04	–12.0	0.18	0.19
ROA	0.09	0.12	5,571	0.13	0.11	5,558	–0.03	–15.2	0.09	0.11
Sales Growth	0.22	0.50	5,253	0.17	0.38	5,291	0.05	5.5	0.14	0.38
SG&A to Sales	0.41	0.27	5,248	0.35	0.24	5,320	0.06	11.6	0.28	0.20
Depreciation & Amortization to Sales	0.07	0.10	5,571	0.07	0.10	5,558	0.00	1.0	0.06	0.08
R&D to Assets	0.11	0.11	4,507	0.07	0.08	3,918	0.03	15.4	0.06	0.08
CAPEX to Assets	0.05	0.06	5,561	0.05	0.06	5,553	–0.00	–1.2	0.04	0.06
Firm Age	24.45	17.55	5,578	26.76	18.30	5,578	–2.32	–6.8	26.76	20.40

Note: This table reports the summary statistics for the treated and control firms in the year prior to the treatment (i.e., the year for which firm characteristics are used in the matching procedure) and also for all firms in Compustat.

Table 3: Double-difference regressions

	(1) Gross Margin	(2) Operating Margin	(3) ROA	(4) Sales Growth
Post	-0.007***	-0.008***	-0.007***	-0.022***
	(-4.08)	(-4.47)	(-5.61)	(-5.50)
DirectTreated × Post	0.008**	0.014***	0.009***	-0.025***
	(2.29)	(3.84)	(3.41)	(-2.75)
IndirectTreated × Post	0.004*	0.008***	0.006***	-0.005
	(1.81)	(3.38)	(3.74)	(-0.90)
Observations	68,682	68,526	68,594	67,018
Firm × Cohort FE	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1
Adjusted R-squared	0.878	0.746	0.667	0.321
P-value from a Test of DirectTreated × Post = IndirectTreated × Post	0.26	0.09	0.36	0.03

Note: This table reports estimates from the following regression using the sample of all events,

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $DirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms that experience a direct board connection to a product market peer while $IndirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms that experience a new indirect board connection to a product market peer. $DirectTreated_{i,c} \times Post_{c,t}$ and $IndirectTreated_{i,c} \times Post_{c,t}$ are the double-difference terms, the coefficient estimates of which are the estimated effects of new board connections to product market peers. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$. We also report the p-value from a test for the equality of the effects of direct connections and the effects of indirect connections. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Double-difference regressions, using non-focal-firm initiated board connections

	Gross Margin	Operating Margin	ROA
Panel A: Using all non-focal-firm initiated events			
Post	–0.006**	–0.011***	–0.009***
	(–2.45)	(–3.88)	(–4.30)
NFFInitiatedTreated × Post	0.007**	0.010***	0.009***
	(2.02)	(2.79)	(3.50)
Observations	26,060	26,010	26,026
Adjusted R-sqaured	0.894	0.764	0.696
Panel B: Require that the intermediate firm is not a product market peer of the treated firm			
Post	–0.009***	–0.011***	–0.008***
	(–2.96)	(–3.51)	(–3.37)
NFFInitiatedTreated × Post	0.007*	0.010***	0.008***
	(1.94)	(2.61)	(2.64)
Observations	16,927	16,905	16,913
Adjusted R-sqaured	0.909	0.777	0.702
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: Panel A of this table reports estimates from the following regression using the subset of events that are non-focal-firm initiated,

$$Y_{i,j,c,t} \quad = \quad \alpha_1 \times Post_{c,t} + \beta_1 \times NFFInitiatedTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Panel B reports estimates from the above regression using non-focal-firm initiated board connections for which the intermediate firm is not a product market peer of the treated firm. Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $NFFInitiatedTreated_{i,c} \times Post_{c,t}$ is the double-difference term, the coefficient of which is the estimated effects of non-focal-firm initiated new board connections with peer firms. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Effects on product market price and quantity using barcode-level data

	(1) Price Index	(2) Price Index	(3) Price Index	(4) Quantity Index	(5) Quantity Index	(6) Quantity Index
DirectTreated × Post	0.00220***	0.00174*	0.00166*	-0.02093***	-0.01941***	-0.01930***
	(2.73)	(1.89)	(1.80)	(-3.05)	(-2.72)	(-2.75)
IndirectTreated × Post	0.00066***	0.00059***	0.00058***	-0.00809***	-0.00781***	-0.00742***
	(2.61)	(2.58)	(2.54)	(-7.69)	(-7.37)	(-7.13)
Observations	42,737,380	42,714,241	42,650,014	42,737,380	42,714,241	42,650,014
Firm × Product Module × Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%	10%	5%	3%
Adjusted R-squared	0.390	0.391	0.391	0.634	0.635	0.636

Note: This table reports estimates from the following regression,

$$Y_{i,c,z,t} = \alpha_1 \times DirectTreated_{i,c,z} \times Post_{i,c,z,t} + \alpha_2 \times IndirectTreated_{i,c,z} \times Post_{i,c,z,t} + \theta_{i,c,z} + \theta_{c,t} + \theta_{i,t} + \theta_{z,t} + e_{i,c,z,t},$$

where $y_{i,c,z,t}$ is the price index $p_{i,c,z,t}$ or quantity index $q_{i,c,z,t}$ of firm i in product module c in 3-digit zip code area z in quarter t. $DirectTreated_{i,c,z} \times Post_{i,c,z,t}$ ($IndirectTreated_{i,c,z} \times Post_{i,c,z,t}$) equals zero for those firm-product-module-zip3 combinations that are never treated and for treated firm-product-module-zip3 in quarters prior to the treatment of direct (indirect) board connections and equals one for treated firm-product-module-zip3 in quarters post the treatment. $\theta_{i,c,z}$ are firm times product module times zip3 fixed effects. $\theta_{c,t}$ are product module times quarter fixed effects. $\theta_{i,t}$ are firm times quarter fixed effects. $\theta_{z,t}$ are area times quarter fixed effects. In columns (1)-(3) we use price index as the outcome variable and in columns (4)-(6) we use quantity index instead. T-stats are in parentheses. Standard errors are clustered at the firm-pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Effects on cosine similarity of geographic distribution using barcode-level data

	(1) Similarity by Zip-3	(2) Similarity by County	(3) Similarity by DMA
DirectTreated × Post	0.0048	0.0033	0.0053
	(0.87)	(0.64)	(0.94)
IndirectTreated × Post	-0.0037**	-0.0051***	-0.0044***
	(-2.35)	(-3.91)	(-2.66)
Observations	23,051,386	23,051,386	23,051,386
Firm-Pair FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Clustering	Firm-Pair	Firm-Pair	Firm-Pair
Adjusted R-squared	0.878	0.892	0.873

Note: This table reports estimates from the following regression,

$$s_{i,j,t} = \alpha_1 \times DirectTreated_{i,j} \times Post_{i,j,t} + \alpha_2 \times IndirectTreated_{i,j} \times Post_{i,j,t} + \theta_t + \theta_{i,j} + e_{i,j,t}$$

where i and j are indices for the pair firm i and firm j and t is the index for the quarter. $DirectTreated_{i,j} \times Post_{i,j,t}$ ($IndirectTreated_{i,j} \times Post_{i,j,t}$) equals zero for those firm-pairs that are never treated and for treated firm-pairs in quarters prior to the treatment of direct (indirect) board connections and equals one for treated firm-pairs in quarters post the treatment. We include firm-pair fixed effects $\theta_{i,j}$ and quarter fixed effects θ_t. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Cross-sectional heterogeneities in the effects of new board connections

	Gross Margin	Operating Margin	ROA
Panel A: By whether corporate opportunity waivers (COWs) are in effect			
Treated × Post	–0.001	–0.003	0.001
	(–0.73)	(–0.61)	(0.36)
Treated × Post × COWs In Effect	0.008	0.017***	0.009*
	(1.62)	(3.23)	(2.16)
Observations	68,669	68,508	68,576
Panel B: By whether newly connected firm-pairs share major corporate customers			
Treated × Post	0.004	0.009***	0.007***
	(1.51)	(3.39)	(3.77)
Treated × Post × If Share Major Customers	0.013	0.018**	0.010
	(1.39)	(1.96)	(1.59)
Observations	68,669	68,508	68,576
Panel C: By similarity in business descriptions between newly connected firm-pairs			
Treated × Post	0.002	0.006**	0.005**
	(0.93)	(2.34)	(2.56)
Treated × Post × Top Similarity	0.008	0.013**	0.009**
	(1.45)	(2.50)	(2.53)
Observations	68,669	68,508	68,576
Panel D: By HHI of the treated firm's industry			
Treated × Post	0.003	0.008**	0.007***
	(1.06)	(2.45)	(2.82)
Treated × Post × Top HHI	0.003	0.003	0.002
	(0.74)	(0.77)	(0.56)
Observations	68,512	68,351	68,406
Panel E: By returns to scale of the treated firm's industry			
Treated × Post	0.004	0.006*	0.005*
	(1.52)	(1.85)	(1.90)
Treated × Post × Top Returns to Scale	0.003	0.009*	0.005
	(0.79)	(1.82)	(1.47)
Observations	64,997	64,854	64,894
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: This table reports estimates from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times Post_{c,t} \times EventCharacteristic_c + \beta_1 \times Treated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $Treated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to product market peers, and zero otherwise. In this regression we pool events of new direct and indirect connections together. $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. $EventCharacteristic_c$ is a sorting variable in the cross-section. It equals one for the time series of both the treated firm and its control if COWs are in effect in the event year in the state where the treated firm was incorporated, the newly connected firms share common corporate customers, or are in the top or bottom half in terms of a certain characteristic. $Treated_{i,c} \times Post_{c,t}$ is the double-difference term, the coefficient of which is the estimated effects of new connections in the subsample where $EventCharacteristic_c$ takes the value of zero. $EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t}$ is the triple-difference term, the coefficient of which is the estimated incremental effects of new connections where $EventCharacteristic_c$ takes the value of one relative to where $EventCharacteristic_c$ takes the value of zero. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$, $EventCharacteristic_c$, and $EventCharacteristic_c \times Treated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. For brevity, only coefficients of the double-difference and triple-difference terms are reported in the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Robustness to controlling for other inter-firm relationships

	Gross Margin	Operating Margin	ROA
Panel A: Control for customer-supplier relationships			
NonCusSupTreated × Post	0.004*	0.010***	0.007***
	(1.89)	(3.87)	(4.10)
CusSupTreated × Post	0.005	0.020**	0.019***
	(0.82)	(2.19)	(3.37)
Observations	68,669	68,508	68,576
Panel B: Control for joint ventures and strategic alliance			
NonAllianceTreated × Post	0.004*	0.010***	0.008***
	(1.88)	(4.02)	(4.42)
AllianceTreated × Post	0.005	0.002	–0.004
	(0.65)	(0.31)	(–0.82)
Observations	68,669	68,508	68,576
Panel C: Control for CO to all peers using kappa, κ (Amel-Zadeh et al., 2022)			
Treated × Post	0.005	0.009*	0.007*
	(1.00)	(1.69)	(1.82)
Δ(Common Ownership) × Post	0.000	0.005**	0.004*
	(0.20)	(2.11)	(1.88)
Observations	8,636	8,625	8,625
Panel D: Control for CO to all peers using GGL_{linear} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.009***
	(1.24)	(3.17)	(3.52)
Δ(Common Ownership) × Post	0.004***	0.005***	0.004***
	(2.68)	(3.74)	(3.58)
Observations	40,401	40,295	8,625
Panel E: Control for CO to all peers using GGL_{fitted} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.009***
	(1.25)	(3.18)	(3.53)
Δ(Common Ownership) × Post	0.006***	0.008***	0.004***
	(4.71)	(5.82)	(3.63)
Observations	40,401	40,295	40,336

Table 8: Robustness to controlling for other inter-firm relationships

	Gross Margin	Operating Margin	ROA
Panel F: Control for CO to all peers using GGL_{full_attn} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.009***
	(1.24)	(3.17)	(3.53)
Δ(Common Ownership) × Post	0.003***	0.003**	0.000
	(3.05)	(2.02)	(0.34)
Observations	40,401	40,295	40,336
Panel G: Control for CO to new connections using GGL_{linear} (Gilje et al., 2020)			
Treated × Post	0.005	0.011***	0.008***
	(1.56)	(3.45)	(3.52)
Δ(Common Ownership) × Post	–0.001	–0.001	–0.000
	(–0.87)	(–1.02)	(–1.20)
Observations	41,151	41,044	4,449
Panel H: Control for CO to new connections using GGL_{fitted} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.008***
	(1.45)	(3.20)	(3.36)
Δ(Common Ownership) × Post	0.001	0.002	0.001
	(0.71)	(1.32)	(0.69)
Observations	41,151	41,044	41,083
Panel I: Control for CO to new connections using GGL_{full_attn} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.009***
	(1.35)	(3.26)	(3.46)
Δ(Common Ownership) × Post	0.001	0.000	–0.000
	(0.79)	(0.37)	(–0.32)
Observations	41,151	41,044	41,083
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: Panel A of this table reports estimates from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times NonCusSupTreated_{i,c} \times Post_{c,t} + \beta_2 \times CusSupTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $NonCusSupTreated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to a product market peer that is not its customer or supplier firm. $CusSupTreated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to a product market peer that is also a customer or supplier firm of its. Panel B of this table reports estimates from the following regression

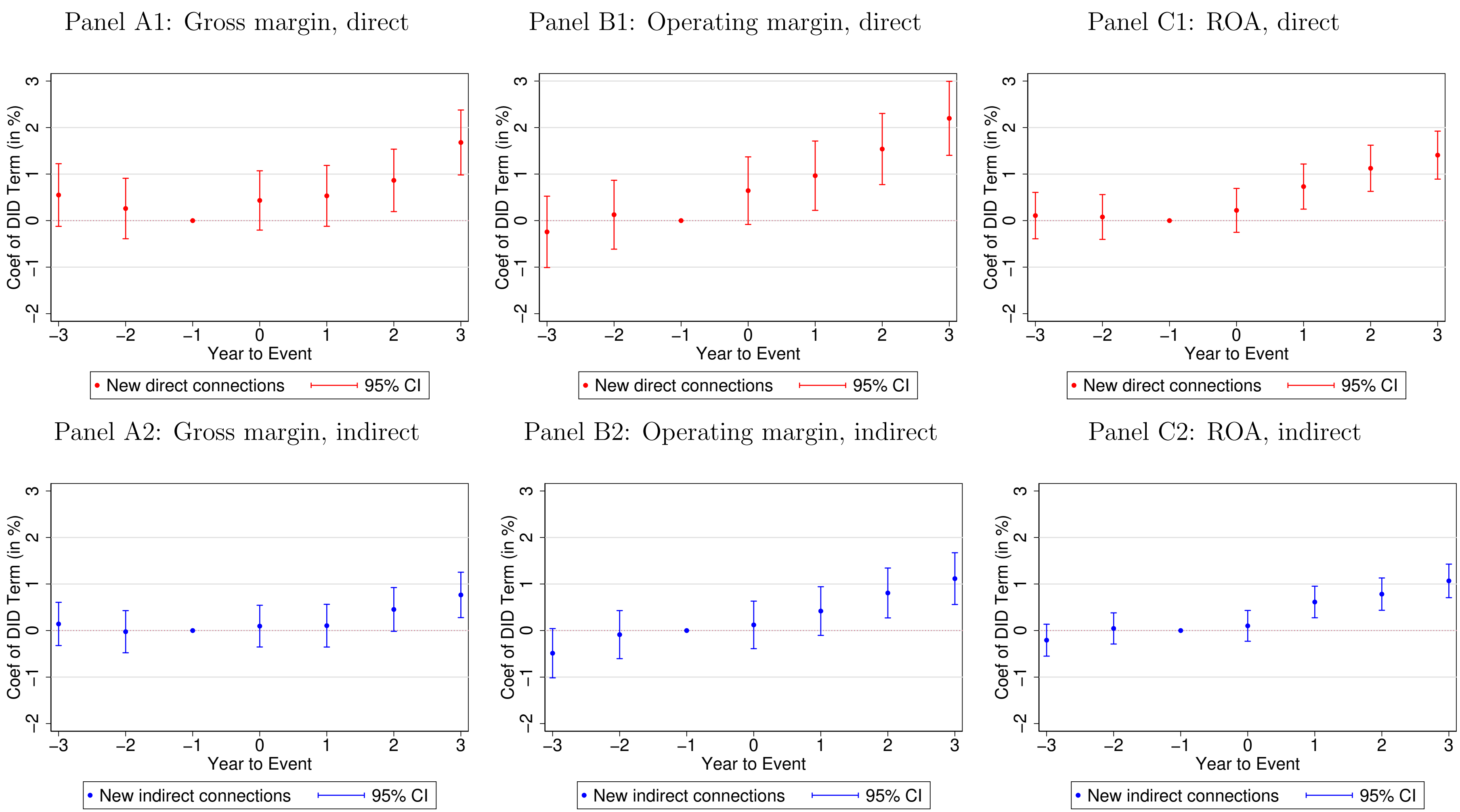
$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times NonAllianceTreated_{i,c} \times Post_{c,t} + \beta_2 \times AllianceTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $NonAllianceTreated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to a product market peer that it never formed strategic alliance or started joint venture with during the sample period. $AllianceTreated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to a product market peer that it ever formed strategic alliance or started joint venture with during the sample period. Panels C to I of this table reports estimates from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times Treated_{i,c} \times Post_{c,t} + \gamma_1 \times \Delta(CommonOwnership)_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

To obtain $\Delta(CommonOwnership)_{i,c}$, in Panels C to F we calculate the mean of common ownership (CO) between a treated or control firm and all of its Hoberg-Phillips product market peers during [0, +3] minus the mean during [-3, -1]. In Panels H to I, we calculate the mean of common ownership (CO) between a treated firm and its newly connected product market peers during [0, +3] minus the mean during [-3, -1]. $\Delta(CommonOwnership)_{i,c}$ is a constant for each time series of seven years (from τ = -3 to +3). We then scale it by its sample standard deviation. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. In these regressions we pool events of new direct and indirect connections together. $Treated_{i,c}$, $NonCusSupTreated_{i,c}$, $CusSupTreated_{i,c}$, $NonAllianceTreated_{i,c}$, $AllianceTreated_{i,c}$, $\Delta(CommonOwnership)_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. For brevity, we omit coefficients of $Post_{c,t}$ from the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1: Plots of the dynamics of the difference between treated and control firms

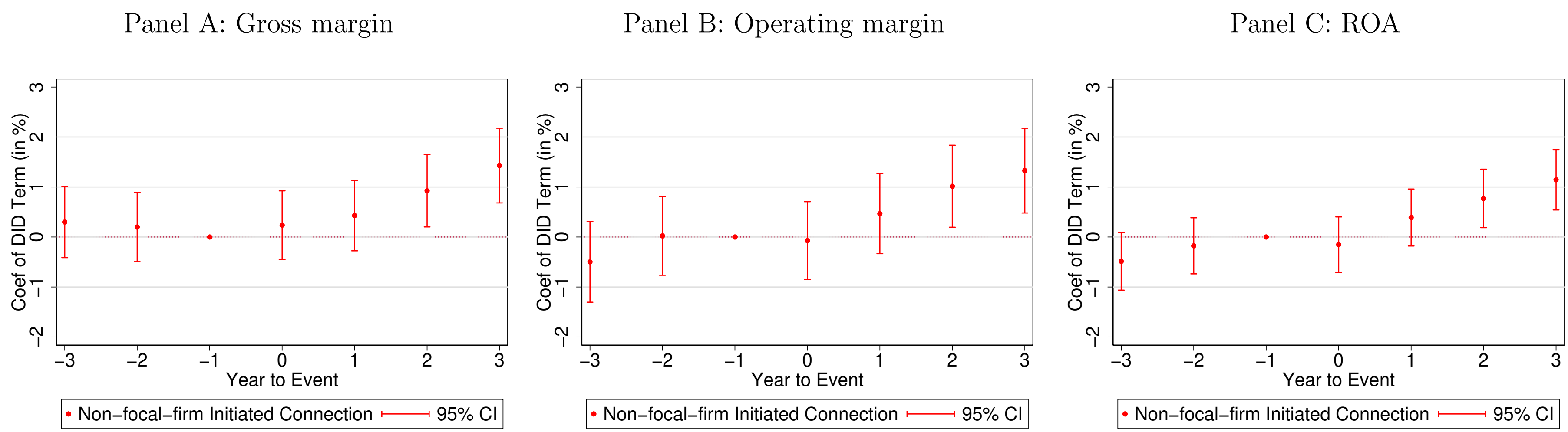


Note: This figure plots coefficients from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\ &+ \mathit{DirectTreated}_{i,c} \times (\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}) \\ &+ \mathit{IndirectTreated}_{i,c} \times (\sum_{s=-3}^{-2} \delta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \delta_s \times \mathbb{1}(\tau = s)_{c,t}) \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here t represents the calendar year and τ represents the year relative to the treatment. $\mathbb{1}(\tau = s)_{c,t}$ is a dummy variable that is equal to one if the observation is $-s$ years before the treatment (for $s = -3, -2$) or if the observation is s years after the treatment (for $s = 0, 1, 2, 3$). We omit the dummy variables for the year prior to the event, i.e., $\tau = -1$, which forms the baseline year. Thus all the effects we document are relative to this year. The estimates of γ_s and δ_s capture the difference in outcome variables between treated and control firms $-s$ years before the treatment (for $s = -3, -2$) or s years after the treatment (for $s = 0, 1, 2, 3$) relative to their difference in the baseline year. $\mathit{DirectTreated}_{i,c}$ and $\mathit{IndirectTreated}_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. Standard errors are clustered at the firm level.

Figure 2: Plots of the dynamics of the difference between treated and control firms, using the non-focal-firm initiated board connections



Note: This figure plots coefficients from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} &= \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
&+ \; NFFInitiatedTreated_{i,c} \times (\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}) + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

Here t represents the calendar year and τ represents the year relative to the treatment. $\mathbb{1}(\tau = s)_{c,t}$ is a dummy variable that is equal to one if the observation is $-s$ years before the treatment (for $s = -3, -2$) or if the observation is s years after the treatment (for $s = 0, 1, 2, 3$). We omit the dummy variables for the year prior to the event, i.e., $\tau = -1$, which forms the baseline year. Thus all the effects we document are relative to this year. The estimates of γ_s capture the difference in outcome variables between treated and control firms $-s$ years before the treatment (for $s = -3, -2$) or s years after the treatment (for $s = 0, 1, 2, 3$) relative to their differences in the baseline year. $NFFInitiatedTreated_{i,c}$ is left out of the regressions as they are absorbed by $\theta_{i,c}$. Standard errors are clustered at the firm level.

Internet Appendix

IA.1 Supplementary Tables and Figures

Table A1: List of variables

Panel A: Financial and accounting variables	
Assets	The natural logarithm of the firm's total assets (*log(at)*)
Gross Margin	The ratio of gross profit to sales (*gp/sale*)
Operating Margin	The ratio of operating income before depreciation and amortization to sales (*oibdp/sale*)
ROA	The ratio of operating income before depreciation and amortization to total assets (*oibdp/at*)
Sales Growth	The percentage change of sales relative to the prior year (*(sale-l.sale)/l.sale*)
Panel B: Indicator variables used in regressions	
DirectTreated	A dummy variable that equals one for the time series of a firm forming new direct connections to product market peers
IndirectTreated	A dummy variable that equals one for the time series of a firm forming new indirect connections to product market peers
Post	A dummy variable that equals zero for τ = -3, -2, -1, and equals one for τ = 0, 1, 2, and 3, where τ is the event year
NFFInitiatedTreated	A dummy variable that equals one for the time series of a firm forming non-focal-firm initiated new board connections to product market peers
M&AInducedTreated	A dummy variable that equals one for the time series of a firm forming merger-induced new board connections to product market peers
PseudoDirectTreated	A dummy variable that equals one for the time series of a firm forming direct connections to pseudo industry peers
PseudoIndirectTreated	A dummy variable that equals one for the time series of a firm forming indirect connections to pseudo industry peers

Table A1: List of variables (continued)

Panel C: Sorting variables	
If Share Major Customers	Whether the connected firm-pair has common major customer firms, i.e., those accounting for more than 10% of their total sales according to their annual disclosure
Similarity Score	The cosine similarity scores between the treated firm and its new connections (Hoberg and Phillips, 2010, 2016). If an event involves a new connection between a treated firm and multiple product market peers, it takes the value of the largest cosine similarity score
Top Similarity	A dummy that equals one for the time series of both the treated firm and its control if the new connections are in the top half in terms of the cosine similarity score between the treated firm and its new connections, and some new connections are in the same SIC-3 industry as the treated firm
HHI	The Herfindahl-Hirschman index of the text-based industry that the treated firm is in (Hoberg and Phillips, 2016)
Top HHI	A dummy that equals one for the time series of both the treated firm and its control if the treated firm is in the top half in terms of HHI among all treated firms treated in the same year
Returns to Scale	The estimated returns to scale of the industry that the treated firm is in. Following Dong et al. (2019), we estimate a two-factor Cobb-Douglas production function for each SIC-2 industry using data of the year 1999 and OLS regressions. We proxy for the firm's output by its sales (*sale*), the firm's labor by the number of its employees (*emp*), and the firm's capital by its property, plant, and equipment (*ppent*). We then add up the coefficients for the proxies for labor and capital, which is our measure of an industry's returns to scale
Top Returns to Scale	A dummy that equals one for the time series of both the treated firm and its control if the industry of the treated firm is in the top half in terms of Returns to Scale

Table A1: List of variables (continued)

Panel D: Other variables	
κ	The firm-pair-year level measure of common ownership developed in Amel-Zadeh et al. (2022)
GGL_{linear}	The firm-pair-year level measure of common ownership developed in Gilje et al. (2020)
GGL_{fitted}	A version of common ownership measure developed in Gilje et al. (2020) that uses a non-parametric fitted attention function estimated with voting data
GGL_{full_attn}	A version of common ownership measure developed in Gilje et al. (2020) that assumes full attention, i.e., $g = 1$
$\Delta(CommonOwnership)$	The change in the within-industry common ownership, i.e., the mean common ownership between a firm and its product market peers from $\tau = -3, -2, -1$ to $\tau = 0, 1, 2, 3$. We calculate both $\Delta(CommonOwnership)$ to all of a firm's Hoberg-Phillips product market peers and also $\Delta(CommonOwnership)$ to a firm's newly connected product market peers. For the former, for each treated firm, we calculate the average common ownership measure between the firm and all of its Hoberg-Phillips product market peers. We do it separately for each year from $\tau = -3$ to $\tau = 3$. Then we take a prior-event average using $\tau = -3, -2, -1$, and a post-event average using $\tau = 0, 1, 2, 3$, and take the post-minus-prior difference. We arrive at a constant for each time series of length 7 (from τ = -3 to +3). We do the same calculation for each control firm around the treatment year of the treated firm it is matched to. Finally, we scale this measure by its sample standard deviation. For the latter, we do the same calculation for treated firms but using the common ownership measure to its newly connected product market peers only. For control firms, we set $\Delta(CommonOwnership)$ to 0

Table A2: Characteristics of directors involved in board connections

	Connected Directors			Other Directors		
	Mean	SD	N	Mean	SD	N
Age	58.6	8.3	6,999	59.1	9.4	39,555
Is Female	0.12		6,999	0.10		39,555
Is Non-Executive Director	0.89		6,999	0.81		39,555
Total Number of Seats	3.1	1.3	6,999	1.8	1.1	39,555
Years of Experience	30.3	9.6	6,999	30.6	10.6	39,555
Highest Education Degree						
Undergraduate	30.3%			31.8%		
Master	48.3%			45.6%		
Doctoral	21.4%			22.6%		
Total	100%		6,780	100%		36,793
Source of Nomination						
Nominated by Search Firms	26.5%			24.4%		
CEO Recommendation	8.5%			8.9%		
Nominated by Other Insiders	3.4%			1.8%		
Nominated by Independent Directors	8.1%			9.4%		
Merger	2.6%			4.7%		
Nominated by Shareholders	1.3%			1.5%		
Promotion	2.8%			3.3%		
Nominated by the Nominating Committee	46.8%			46.0%		
Total	100%		468	100%		2,361

Note: This table reports the characteristics of directors in treated firms that are involved in the board connections and of other directors in the treated firms. *Age*, *Is Female*, *Is Non-Executive Director*, *Total Number of Seats*, *Years of Experience*, and *Highest Education Degree* are based on BoardEx. *Years of Experience* is the number of years since the director first served any role that is recorded in BoardEx. *Total Number of Seats* is the number of board seats in different firms that a director simultaneously holds in the treatment year. *Source of nomination* uses the board of directors nomination data constructed in Akyol and Cohen (2013).

Table A3: Double-difference regressions, using other outcome variables

	(1) ln(Sales)	(2) ln(COGS)	(3) ln(SG&A)	(4) Markup	(5) ln(Assets)	(6) ln(CAPEX)	(7) ln(R&D)	(8) Tobin's Q
Post	-0.014**	-0.003	0.000	-0.019***	-0.004	-0.012	0.008	-0.044**
	(-2.31)	(-0.33)	(0.01)	(-4.43)	(-0.53)	(-1.09)	(0.81)	(-2.10)
DirectTreated × Post	0.028*	0.024	0.013	0.021***	-0.010	-0.009	-0.021	-0.046
	(1.80)	(1.27)	(0.83)	(2.59)	(-0.56)	(-0.36)	(-1.00)	(-0.99)
IndirectTreated × Post	0.002	-0.005	-0.013	0.019***	-0.026**	-0.045**	-0.021	-0.052*
	(0.13)	(-0.37)	(-1.16)	(3.03)	(-2.01)	(-2.51)	(-1.34)	(-1.71)
Observations	68,669	68,633	65,638	48,272	68,745	68,266	44,202	67,878
Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1	1	1	1	1
Adjusted R-squared	0.977	0.971	0.975	0.905	0.970	0.934	0.967	0.691

Note: This table reports estimates from the following regression using the sample of all events,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Column (1) uses $ln(Sales)$, the natural logarithm of total sales ($sale$) as the outcome variable. Column (2) uses the logarithm of the cost of good sold ($cogs$). Column (3) uses the logarithm of selling, general and administrative costs ($xsga$). Column (4) uses the markup calculated using the cost share approach and adjusting for intangible capital, following Peters and Taylor (2017) and Ayyagari et al. (2023). Column (5) uses the logarithm of assets (at). Column (6) uses the logarithm of capital expenditure ($capex$). Column (7) uses the logarithm of R&D expenditure (xrd). Column (8) uses Tobin's Q. All outcome variables are winsorized at their 1% and 99% percentiles. $DirectTreated_{i,c}$ and $IndirectTreated_{i,c}$ are left out of the regressions as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Double-difference regressions, using merger-induced board connections

	Gross Margin	Operating Margin	ROA
Panel A: Baseline matching scheme			
Post	0.002	–0.008	–0.004
	(0.24)	(–0.73)	(–0.49)
M&AInducedTreated × Post	0.002	0.031**	0.028**
	(0.15)	(2.02)	(2.56)
Observations	1,279	1,279	1,279
Adjusted R-sqaured	0.918	0.766	0.656
Panel B: Require that control firm directors also cross-sit on M&A firms			
Post	0.009	0.015	0.011
	(1.04)	(1.15)	(1.35)
M&AInducedTreated × Post	0.009	0.034*	0.025**
	(0.64)	(1.89)	(2.17)
Observations	1,420	1,420	1,420
Adjusted R-sqaured	0.902	0.757	0.742
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	3	3	3

Note: This table reports estimates from the following regression using the merger-induced board connections,

$$Y_{i,j,c,t} \quad = \quad \alpha_1 \times Post_{c,t} + \beta_1 \times M\&AInducedTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $M\&AInducedTreated_{i,c} \times Post_{c,t}$ is the double-difference term, the coefficient of which is the estimated effects of merger-induced new board connection with peer firms. Panel A uses the same matching procedure as described in Section 2.2. To address the concern that mergers might have spillover effects, Panel B further requires in the matching procedure that the control firm has a director who cross-sits on the board of a firm experiencing merger, but such a merger does not lead to new board connections of the control firm to its product market peers. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. $M\&AInducedTreated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Effects on product market price and quantity using barcode-level data and the coarser "product group" as the product category

	(1) Price Index	(2) Price Index	(3) Price Index	(4) Quantity Index	(5) Quantity Index	(6) Quantity Index
DirectTreated × Post	0.00140*	0.00101	0.00058	-0.00386	-0.00287	-0.00390
	(1.69)	(1.27)	(0.81)	(-0.84)	(-0.63)	(-1.01)
IndirectTreated × Post	0.00033*	0.00025	0.00016	-0.00361***	-0.00338***	-0.00288***
	(1.81)	(1.48)	(1.03)	(-3.24)	(-3.25)	(-3.04)
Observations	32,518,690	32,834,146	33,417,503	32,518,690	32,834,146	33,417,503
Firm × Product Group × Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Product Group × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Threshold on Market Share	5%	3%	1%	5%	3%	1%
Adjusted R-squared	0.344	0.340	0.336	0.569	0.571	0.570

Note: This table reports estimates from the following regression,

$$Y_{i,c,z,t} = \alpha_1 \times DirectTreated_{i,c,z} \times Post_{i,c,z,t} + \alpha_2 \times IndirectTreated_{i,c,z} \times Post_{i,c,z,t} + \theta_{i,c,z} + \theta_{c,t} + \theta_{i,t} + \theta_{z,t} + e_{i,c,z,t},$$

where $y_{i,c,z,t}$ is the price index $p_{i,c,z,t}$ or quantity index $q_{i,c,z,t}$ of firm i in product group c in 3-digit zip code area z in quarter t. $DirectTreated_{i,c,z} \times Post_{i,c,z,t}$ ($IndirectTreated_{i,c,z} \times Post_{i,c,z,t}$) equals zero for those firm-product-group-zip3 combinations that are never treated and for treated firm-product-group-zip3 in quarters prior to the treatment of direct (indirect) board connections and equals one for treated firm-product-group-zip3 in quarters post the treatment. $\theta_{i,c,z}$ are firm times product group times zip3 fixed effects. $\theta_{c,t}$ are product group times quarter fixed effects. $\theta_{i,t}$ are firm times quarter fixed effects. $\theta_{z,t}$ are area times quarter fixed effects. In columns (1)-(3) we use price index as the outcome variable and in columns (4)-(6) we use quantity index instead. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Effects on product market price and quantity using barcode-level data, using the non-focal-firm initiated subset of events

	(1) Price Index	(2) Price Index	(3) Price Index	(4) Quantity Index	(5) Quantity Index	(6) Quantity Index
NFFInitiatedTreated × Post	0.00090***	0.00090***	0.00090***	-0.00665***	-0.00631***	-0.00617***
	(2.41)	(2.42)	(2.43)	(-4.56)	(-4.38)	(-4.32)
Observations	39,815,745	39,726,898	39,663,464	39,815,745	39,726,898	39,663,464
Firm × Product Module × Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Threshold on Market Share	5%	3%	1%	5%	3%	1%
Adjusted R-squared	0.397	0.399	0.399	0.637	0.639	0.639

Note: This table reports estimates from the following regression,

$$Y_{i,c,z,t} = \alpha \times NFFInitiatedTreated_{i,c,z} \times Post_{i,c,z,t} + \theta_{i,c,z} + \theta_{c,t} + \theta_{i,t} + \theta_{z,t} + e_{i,c,z,t},$$

where $y_{i,c,z,t}$ is the price index $p_{i,c,z,t}$ or quantity index $q_{i,c,z,t}$ of firm i in product module c in 3-digit zip code area z in quarter t. For treated firms, we only include observations of those for which the new board connections are non-focal-firm initiated. $NFFInitiatedTreated_{i,c,z} \times Post_{i,c,z,t}$ equals zero for those firm-product-module-zip3 combinations that are never treated and for treated firm-product-module-zip3 in quarters prior to the treatment and equals one for treated firm-product-module-zip3 in quarters post the treatment. $\theta_{i,c,z}$ are firm times product module times zip3 fixed effects. $\theta_{c,t}$ are product module times quarter fixed effects. $\theta_{i,t}$ are firm times quarter fixed effects. $\theta_{z,t}$ are area times quarter fixed effects. In columns (1)-(3) we use price index as the outcome variable and in columns (4)-(6) we use quantity index instead. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Corporate Opportunity Waivers (COWs) and the frequency of board connections

	(1)
	Prob. of forming new connection
COWs In Effect	0.023***
	(3.95)
Observations	55,880
Firm FE	Yes
FF48 × Year FE	Yes
Clustering	Firm

Note: This table reports estimates from the following Probit regression

$$\mathbb{1}(\text{Forming a new board connection to a product market peer})_{i,j,t} = \beta \times COWsInEffect_{i,t} + \theta_i + \theta_{j,t} + e_{i,j,t}.$$

Here $COWsInEffect_{i,t}$ equals one if COWs are in effect in year t in the state where firm i was incorporated. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Robustness to alternative industry classification

	Gross Margin	Operating Margin	ROA
Panel A: Using FactSet to identify peer firms			
DirectTreated × Post	0.006	0.017**	0.012**
	(0.92)	(2.10)	(2.28)
IndirectTreated × Post	0.003	0.009**	0.007***
	(0.91)	(2.50)	(2.90)
Observations	20,998	20,521	20,539
Panel B: Using SIC-3 to identify peer firms			
DirectTreated × Post	0.004	0.015***	0.012***
	(1.38)	(4.04)	(4.73)
IndirectTreated × Post	0.004*	0.010***	0.009***
	(1.93)	(4.38)	(5.25)
Observations	81,325	81,146	81,229
Panel C: Using SIC-4 to identify peer firms			
DirectTreated × Post	0.003	0.013***	0.007**
	(0.77)	(2.79)	(2.39)
IndirectTreated × Post	0.007***	0.010***	0.007***
	(2.72)	(3.58)	(3.64)
Observations	53,054	52,944	53,009
Panel D: Using GICS-6 to identify peer firms			
DirectTreated × Post	0.004*	0.007***	0.004**
	(1.71)	(2.82)	(2.12)
IndirectTreated × Post	0.003**	0.005**	0.004**
	(2.01)	(2.47)	(2.48)
Observations	100,931	100,751	100,817
Panel E: Using GICS-8 to identify peer firms			
DirectTreated × Post	0.005	0.009***	0.006**
	(1.46)	(2.66)	(2.31)
IndirectTreated × Post	0.003*	0.006***	0.006***
	(1.71)	(2.82)	(3.62)
Observations	72,080	71,937	71,985

Note: This table repors estimates for the regression in Table 3 if alternative industry classifications are used in the definition of product market peers when constructing events of board connections. Panel A uses the competitors disclosed by firms and recorded in FactSet Supply Chain Relationships database. Panel B uses SIC-3 industry. Panel C uses SIC-4 industry. Panel D uses GICS 6-digit industry. Panel E uses GICS 8-digit industry.

Table A9: A placebo test using non-product market peers

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.003	-0.003	-0.004
	(-0.84)	(-0.76)	(-1.29)
PseudoDirectTreated × Post	0.010	-0.005	-0.001
	(0.54)	(-0.37)	(-0.12)
PseudoIndirectTreated × Post	0.001	0.001	0.004
	(0.16)	(0.20)	(1.00)
Observations	10,326	10,298	10,299
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.906	0.755	0.679

Note: This table reports estimates from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times PseudoDirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times PseudoIndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t} \end{aligned}$$

using the sample of events of connections to pseudo peers and excluding the overlap of pseudo events with actual events. Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $PseudoDirectTreated_{i,c}$ equals one for the time series of a firm forming direct connections to pseudo peers. $PseudoIndirectTreated_{i,c}$ equals one for the time series of a firm forming indirect connections to pseudo peers. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. $PseudoDirectTreated_{i,c}$ and $PseudoIndirectTreated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Robustness to alternative matching schemes

	Gross Margin	Operating Margin	ROA
Panel A: Use two controls for each event			
DirectTreated × Post	0.007**	0.014***	0.010***
	(2.21)	(3.85)	(3.67)
IndirectTreated × Post	0.004*	0.009***	0.008***
	(1.94)	(3.72)	(4.30)
Observations	94,083	93,898	93,986
Panel B: Use three controls for each event			
DirectTreated × Post	0.007**	0.014***	0.010***
	(2.24)	(3.78)	(3.59)
IndirectTreated × Post	0.004*	0.009***	0.007***
	(1.96)	(3.64)	(4.21)
Observations	113,418	113,163	113,257
Panel C: Match additionally on the number of new appointments during the event year			
DirectTreated × Post	0.011**	0.014***	0.008**
	(2.29)	(2.74)	(2.16)
IndirectTreated × Post	0.003	0.010***	0.009***
	(1.14)	(3.04)	(3.25)
Observations	36,707	36,657	36,687
Panel D: Match using Operating Margin instead of Gross Margin			
DirectTreated × Post	0.008**	0.011***	0.006**
	(2.26)	(2.86)	(2.20)
IndirectTreated × Post	0.005**	0.007***	0.006***
	(1.99)	(2.59)	(2.84)
Observations	60,656	60,610	60,661
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Table A10: Robustness to alternative matching schemes (continued)

	Gross Margin	Operating Margin	ROA
Panel E: Match additionally on Operating Margin			
DirectTreated × Post	0.008**	0.011***	0.005*
	(2.05)	(2.67)	(1.79)
IndirectTreated × Post	0.004*	0.006**	0.005**
	(1.78)	(2.37)	(2.29)
Observations	60,626	60,574	60,631
Panel F: Match additionally on Sales Growth			
DirectTreated × Post	0.009**	0.014***	0.009***
	(2.26)	(3.36)	(2.88)
IndirectTreated × Post	0.003	0.008***	0.007***
	(1.26)	(2.99)	(3.69)
Observations	57,872	57,762	57,810
Panel G: Match additionally on ROA			
DirectTreated × Post	0.009**	0.013***	0.006**
	(2.40)	(3.30)	(2.07)
IndirectTreated × Post	0.005**	0.008***	0.005**
	(2.14)	(2.98)	(2.50)
Observations	60,583	60,531	60,597
Panel H: Match additionally on R&D to Assets			
DirectTreated × Post	0.006	0.014***	0.009**
	(1.47)	(3.04)	(2.55)
IndirectTreated × Post	0.003	0.008***	0.007***
	(1.04)	(2.64)	(2.73)
Observations	45,145	45,049	45,090
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Table A10: Robustness to alternative matching schemes (continued)

	Gross Margin	Operating Margin	ROA
Panel I: Match additionally on CAPEX to Assets			
DirectTreated × Post	0.008**	0.013***	0.007**
	(2.14)	(3.30)	(2.51)
IndirectTreated × Post	0.004*	0.009***	0.006***
	(1.76)	(3.26)	(3.24)
Observations	60,492	60,386	60,440
Panel J: Match additionally on all variables			
DirectTreated × Post	0.005	0.009**	0.005
	(1.39)	(2.20)	(1.58)
IndirectTreated × Post	0.003	0.006**	0.004*
	(1.24)	(2.09)	(1.95)
Observations	56,560	56,504	56,554
Panel K: Require that the control firm is never treated during [–3, 3]			
DirectTreated × Post	0.010**	0.015***	0.010***
	(2.46)	(3.45)	(3.04)
IndirectTreated × Post	0.004	0.006*	0.005**
	(1.54)	(1.88)	(1.98)
Observations	52,354	52,191	52,244
Panel L: Require that the control firm is never treated before or during [–3, 3]			
DirectTreated × Post	0.010**	0.017***	0.010***
	(2.52)	(3.64)	(2.85)
IndirectTreated × Post	0.005*	0.008**	0.005*
	(1.79)	(2.27)	(1.89)
Observations	48,558	48,402	48,450
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Note: This table reports estimates for the regression in Table 3 if alternative matching schemes are used. Panel A (B) uses a matching scheme that uses two (three) controls for each treated event. Panel C uses a matching scheme that additionally requires an exact match on the number of new appointments to the board during the event year. Panel D uses a matching scheme that matches on operating margin instead of gross margin. Panel E (F; G; H; I) uses a matching scheme that additionally matches on operating margin (sales growth; ROA; R&D to Assets; CAPEX to Assets). Panel J matches on all variables when R&D is non-missing for the treated firm and on all variables but R&D when it is missing. Panel K uses a matching scheme that additionally requires the control firm being never treated from τ = -3 to +3. Panel L uses a matching scheme that additionally requires the control firm being never treated before or during [–3, 3].

Table A11: Robustness of cross-sectional heterogeneities to alternative matching schemes

	Panel A			Panel B			Panel C			Panel D		
	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA
1. By whether corporate opportunity waivers (COWs) are in effect												
Double Diff.	0.002	0.000	0.002	0.004	0.000	0.002	0.002	0.001	0.002	0.006	–0.001	–0.001
	(0.55)	(0.11)	(0.66)	(0.96)	(0.07)	(0.70)	(0.49)	(0.19)	(0.35)	(1.38)	(–0.18)	(–0.17)
Triple Diff.	0.004	0.013**	0.008**	0.002	0.013***	0.007**	0.004	0.014**	0.009*	–0.000	0.012**	0.009**
	(0.82)	(2.55)	(2.04)	(0.42)	(2.61)	(2.00)	(0.63)	(2.18)	(1.81)	(–0.06)	(2.20)	(2.06)
2. By whether newly connected peers share major corporate customers												
Double Diff.	0.004**	0.009***	0.008***	0.004**	0.009***	0.007***	0.005	0.011***	0.008***	0.005**	0.007***	0.005***
	(2.09)	(3.92)	(4.42)	(2.16)	(3.87)	(4.34)	(1.58)	(3.30)	(3.32)	(2.31)	(2.90)	(2.79)
Triple Diff.	0.010	0.017*	0.010	0.010	0.016*	0.010*	0.012	0.008	0.001	0.004	0.009	0.007
	(1.15)	(1.93)	(1.64)	(1.11)	(1.87)	(1.67)	(0.95)	(0.60)	(0.09)	(0.43)	(0.90)	(0.98)
3. By similarity in business descriptions between newly connected peers												
Double Diff.	0.003	0.007***	0.006***	0.003	0.007***	0.006***	0.003	0.009***	0.007**	0.005**	0.004	0.003
	(1.59)	(2.89)	(3.17)	(1.58)	(2.86)	(3.22)	(1.10)	(2.60)	(2.46)	(2.22)	(1.57)	(1.41)
Triple Diff.	0.006	0.012**	0.008**	0.006	0.012**	0.008**	0.008	0.008	0.006	0.002	0.013***	0.010***
	(1.26)	(2.45)	(2.53)	(1.34)	(2.55)	(2.48)	(1.12)	(1.27)	(1.29)	(0.32)	(2.60)	(2.67)
4. By HHI of the treated firm's industry												
Double Diff.	0.004	0.009***	0.008***	0.004	0.009***	0.008***	0.006	0.011**	0.009***	0.004	0.007**	0.006***
	(1.33)	(2.86)	(3.34)	(1.35)	(2.89)	(3.46)	(1.63)	(2.50)	(2.70)	(1.16)	(1.97)	(2.59)
Triple Diff.	0.003	0.003	0.001	0.003	0.002	0.001	–0.002	0.001	–0.001	0.005	0.003	–0.001
	(0.83)	(0.66)	(0.45)	(0.79)	(0.63)	(0.27)	(–0.37)	(0.13)	(–0.25)	(1.16)	(0.73)	(–0.31)
5. By returns to scale of the treated firm's industry												
Double Diff.	0.003	0.006**	0.005**	0.003	0.005*	0.004*	0.003	0.001	0.001	0.005**	0.005	0.003
	(1.22)	(2.11)	(2.06)	(1.14)	(1.72)	(1.75)	(0.71)	(0.35)	(0.24)	(2.09)	(1.60)	(1.26)
Triple Diff.	0.006	0.009**	0.006*	0.006	0.011**	0.008**	0.006	0.017***	0.013**	0.004	0.009*	0.007*
	(1.56)	(2.02)	(1.81)	(1.62)	(2.41)	(2.21)	(1.02)	(2.64)	(2.50)	(0.98)	(1.88)	(1.80)

Table A11: Robustness of cross-sectional heterogeneities to alternative matching schemes

	Panel E			Panel F			Panel G			Panel H		
	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA
1. By whether corporate opportunity waivers (COWs) are in effect												
Double Diff.	0.005	–0.001	–0.001	0.002	–0.000	–0.000	0.006	0.003	0.000	0.007	0.002	0.004
	(1.22)	(–0.17)	(–0.14)	(0.51)	(–0.07)	(–0.04)	(1.34)	(0.64)	(0.11)	(1.57)	(0.44)	(0.96)
Triple Diff.	–0.000	0.011**	0.007*	0.002	0.014**	0.010*	–0.000	0.009*	0.009**	–0.004	0.010*	0.006
	(–0.02)	(2.05)	(1.67)	(0.34)	(2.19)	(1.94)	(–0.09)	(1.77)	(2.01)	(–0.65)	(1.79)	(1.27)
2. By whether newly connected peers share major corporate customers												
Double Diff.	0.005**	0.007***	0.004**	0.003	0.009***	0.007***	0.005**	0.009***	0.006***	0.004	0.008***	0.007***
	(1.98)	(2.68)	(2.22)	(1.27)	(3.02)	(2.94)	(2.10)	(3.46)	(3.21)	(1.63)	(3.34)	(3.62)
Triple Diff.	0.006	0.008	0.007	0.004	0.009	0.005	0.003	0.012	0.008	0.009	0.013	0.011
	(0.66)	(0.78)	(1.01)	(0.45)	(0.87)	(0.64)	(0.34)	(1.25)	(1.10)	(0.89)	(1.30)	(1.61)
3. By similarity in business descriptions between newly connected peers												
Double Diff.	0.005**	0.004	0.002	0.003	0.006*	0.003	0.004	0.005*	0.004*	0.004	0.005**	0.005**
	(2.26)	(1.51)	(1.06)	(1.20)	(1.73)	(1.23)	(1.51)	(1.93)	(1.71)	(1.61)	(1.97)	(2.41)
Triple Diff.	0.000	0.012**	0.009**	0.002	0.013**	0.013***	0.006	0.016***	0.011***	0.002	0.014***	0.009**
	(0.06)	(2.29)	(2.28)	(0.31)	(2.26)	(2.97)	(0.98)	(3.11)	(2.86)	(0.39)	(2.69)	(2.46)
4. By HHI of the treated firm's industry												
Double Diff.	0.004	0.007*	0.006**	0.003	0.010***	0.009***	0.003	0.009**	0.008***	0.005	0.009**	0.009***
	(1.38)	(1.95)	(2.28)	(0.81)	(2.63)	(2.95)	(1.01)	(2.50)	(2.96)	(1.51)	(2.53)	(3.44)
Triple Diff.	0.002	0.002	–0.002	0.002	–0.001	–0.004	0.004	0.002	–0.001	–0.001	0.001	–0.002
	(0.49)	(0.44)	(–0.51)	(0.46)	(–0.21)	(–0.87)	(1.06)	(0.53)	(–0.42)	(–0.19)	(0.23)	(–0.65)
5. By returns to scale of the treated firm's industry												
Double Diff.	0.004*	0.005	0.003	0.005*	0.007**	0.005	0.004	0.006**	0.003	0.004	0.004	0.004
	(1.82)	(1.61)	(1.01)	(1.93)	(2.04)	(1.61)	(1.58)	(2.01)	(1.27)	(1.48)	(1.30)	(1.34)
Triple Diff.	0.004	0.007	0.006	0.000	0.005	0.005	0.006	0.009*	0.008**	0.004	0.012**	0.009**
	(1.05)	(1.55)	(1.52)	(0.02)	(0.90)	(1.07)	(1.46)	(1.79)	(1.98)	(0.99)	(2.58)	(2.38)

Table A11: Robustness of cross-sectional heterogeneities to alternative matching schemes

	Panel I			Panel J			Panel K			Panel L		
	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA	Gross Margin	Operating Margin	ROA
1. By whether corporate opportunity waivers (COWs) are in effect												
Double Diff.	0.006	0.006	0.002	0.003	–0.001	–0.001	0.005	0.001	0.004	0.006	0.002	0.003
	(1.34)	(1.41)	(0.47)	(0.60)	(–0.20)	(–0.31)	(1.09)	(0.20)	(0.93)	(1.19)	(0.48)	(0.80)
Triple Diff.	0.001	0.004	0.005	0.001	0.010*	0.007*	0.002	0.011**	0.004	0.002	0.011*	0.004
	(0.16)	(0.68)	(1.09)	(0.30)	(1.87)	(1.66)	(0.31)	(2.03)	(0.97)	(0.32)	(1.95)	(0.92)
2. By whether newly connected peers share major corporate customers												
Double Diff.	0.006**	0.009***	0.005**	0.003	0.006**	0.004**	0.005*	0.007**	0.006**	0.006**	0.009***	0.006**
	(2.49)	(3.29)	(2.45)	(1.41)	(2.24)	(1.96)	(1.89)	(2.30)	(2.28)	(2.09)	(2.72)	(2.26)
Triple Diff.	0.003	0.011	0.008	0.002	0.008	0.004	0.009	0.021**	0.013*	0.010	0.020*	0.009
	(0.34)	(1.11)	(1.19)	(0.20)	(0.82)	(0.60)	(0.81)	(2.10)	(1.74)	(0.82)	(1.84)	(1.19)
3. By similarity in business descriptions between newly connected peers												
Double Diff.	0.004*	0.005*	0.003	0.003	0.003	0.002	0.004	0.007**	0.005**	0.005*	0.009***	0.006**
	(1.82)	(1.73)	(1.25)	(1.33)	(0.93)	(0.77)	(1.46)	(2.10)	(2.10)	(1.90)	(2.66)	(2.18)
Triple Diff.	0.006	0.017***	0.009**	0.001	0.014***	0.009**	0.006	0.007	0.004	0.005	0.004	0.002
	(1.17)	(3.14)	(2.48)	(0.23)	(2.61)	(2.30)	(1.07)	(1.31)	(0.99)	(0.75)	(0.74)	(0.39)
4. By HHI of the treated firm's industry												
Double Diff.	0.005	0.008**	0.006**	0.001	0.006	0.006**	0.004	0.008**	0.007**	0.004	0.009**	0.006**
	(1.53)	(2.27)	(2.30)	(0.28)	(1.60)	(2.16)	(1.14)	(2.01)	(2.32)	(1.17)	(2.28)	(2.05)
Triple Diff.	0.002	0.004	–0.001	0.006	0.003	–0.003	0.004	0.002	–0.001	0.005	0.003	0.000
	(0.58)	(0.81)	(–0.22)	(1.38)	(0.56)	(–0.73)	(0.90)	(0.43)	(–0.25)	(1.18)	(0.53)	(0.04)
5. By returns to scale of the treated firm's industry												
Double Diff.	0.005*	0.007**	0.003	0.002	0.004	0.003	0.005*	0.005	0.004	0.006**	0.008**	0.007**
	(1.89)	(2.28)	(1.20)	(0.80)	(1.31)	(1.12)	(1.69)	(1.44)	(1.48)	(2.07)	(2.21)	(2.15)
Triple Diff.	0.005	0.006	0.006	0.006	0.006	0.003	0.004	0.010	0.005	0.004	0.007	0.001
	(1.21)	(1.26)	(1.43)	(1.45)	(1.17)	(0.83)	(0.84)	(1.61)	(1.09)	(0.64)	(1.10)	(0.28)

Note: This table examines the cross-sectional heterogeneities in the effects of board connections under alternative matching schemes. Panels A-L correspond to the alternative matching schemes in Table A10

Table A12: Robustness to alternative regression specifications

	Gross Margin	Operating Margin	ROA
Panel A: Separately estimating effects of direct and indirect connections			
DirectTreated × Post	0.008*	0.011**	0.008**
	(1.94)	(2.57)	(2.46)
IndirectTreated × Post	0.004*	0.009***	0.007***
	(1.75)	(3.48)	(3.68)
Panel B: SIC-3 × Year FE and Firm × Cohort FE			
DirectTreated × Post	0.008**	0.016***	0.011***
	(2.29)	(4.05)	(4.12)
IndirectTreated × Post	0.004*	0.009***	0.009***
	(1.73)	(3.42)	(4.54)
Panel C: FIC-200 × Year FE and Firm × Cohort FE			
DirectTreated × Post	0.009**	0.013***	0.008***
	(2.48)	(3.51)	(2.96)
IndirectTreated × Post	0.003	0.007***	0.006***
	(1.30)	(2.58)	(3.25)
Panel D: Clustering at the connected firm-pair level			
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.18)	(3.48)	(3.24)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.83)	(3.25)	(3.63)

Note: Panel A of this table reports estimates for the regression in Table 3 if the effects of direct and indirect board connections are estimated in two separate regressions. Panels B and C of this table report estimates for the regression in Table 3 if alternative fixed effects are used. Regressions in Panel B use SIC-3 industry times year fixed effects and firm times cohort fixed effects. Regressions in Panel C use FIC-200 industry times year fixed effects and firm times cohort fixed effects. FIC-200 industry classification is provided in the Hoberg-Phillips Data Library. Panel D of this table reports estimates for the regression in Table 3 if alternative clustering of standard errors is used. We cluster the standard errors at the unit level, which we define to be all observations of a connected firm-pair for treated firms and all observations of a single firm for control firms. This method of clustering accounts for the possibility that the outcome variables of connected firm-pairs could be positively correlated.

Table A13: Double-difference regressions by executive versus non-executive directors

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.007***	-0.007***	-0.007***
	(-3.88)	(-4.31)	(-5.50)
DirectTreated, Is Not Exec. × Post	0.007*	0.013***	0.008***
	(1.75)	(3.19)	(2.93)
DirectTreated, Is Exec. × Post	0.008*	0.015**	0.009**
	(1.65)	(2.32)	(1.98)
IndirectTreated, Is Not Exec. × Post	0.001	0.006**	0.006***
	(0.63)	(2.23)	(3.25)
IndirectTreated, Is Exec. × Post	0.008**	0.011***	0.005**
	(2.04)	(2.92)	(2.05)
Observations	68,682	68,526	68,594
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.878	0.746	0.667

Note: This table reports estimates from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} \\ &+ \beta_1 \times DirectTreatedIsNotExec_{i,c} \times Post_{c,t} + \beta_2 \times DirectTreatedIsExec_{i,c} \times Post_{c,t} \\ &+ \beta_3 \times IndirectTreatedIsNotExec_{i,c} \times Post_{c,t} + \beta_4 \times IndirectTreatedIsExec_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $DirectTreatedIsNotExec_{i,c}$ equals one for the time series of a firm forming direct connections to product market peers and only non-executive directors are involved. $DirectTreatedIsExec_{i,c}$ equals one for the time series of a firm forming direct connections to product market peers and directors who are also executives are involved. $IndirectTreatedIsNotExec_{i,c}$ equals one for the time series of a firm forming indirect connections to product market peers and only non-executive directors are involved. $IndirectTreatedIsExec_{i,c}$ equals one for the time series of a firm forming indirect connections to product market peers and directors who are also executives are involved. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. $DirectTreatedIsNotExec_{i,c}$, $DirectTreatedIsExec_{i,c}$, $IndirectTreatedIsNotExec_{i,c}$, and $IndirectTreatedIsExec_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A14: Double-difference regressions by inbound versus outbound directors

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.007***	-0.008***	-0.007***
	(-4.07)	(-4.46)	(-5.60)
DirectTreated, Inbound × Post	0.006	0.014***	0.012***
	(1.40)	(2.91)	(3.68)
DirectTreated, Outbound × Post	0.009**	0.013***	0.005
	(2.03)	(2.58)	(1.34)
IndirectTreated	0.004*	0.008***	0.006***
	(1.81)	(3.38)	(3.74)
Observations	68,682	68,526	68,594
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.878	0.746	0.667

Note: This table reports estimates from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreatedInbound_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times DirectTreatedOutbound_{i,c} \times Post_{c,t} + \beta_3 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $DirectTreatedInbound_{i,c}$ equals one for the time series of a firm forming direct connections to product market peers and the connections are caused by new appointments to the treated firm's board. $DirectTreatedOutbound_{i,c}$ equals one for the time series of a firm forming direct connections to product market peers and the connections are caused by existing directors of the treated firm getting appointed to a peer firm. $IndirectTreated_{i,c}$ equals one for the time series of a firm forming indirect connections to product market peers. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. $DirectTreatedInbound_{i,c}$, $DirectTreatedOutbound_{i,c}$, and $IndirectTreated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A15: Effects of the death of connected directors

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	0.010	-0.004	0.001
	(0.54)	(-0.19)	(0.09)
DeathTreated × Post	-0.018	-0.031*	-0.018**
	(-1.15)	(-1.90)	(-2.17)
Observations	1,137	1,137	1,137
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	3	3	3
Adjusted R-squared	0.855	0.744	0.690

Note: This table reports estimates from the following regression

$$Y_{i,j,c,t} = \alpha_1 \times Post_{c,t} + \beta_1 \times DeathTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Here $DeathTreated_{i,c}$ equals one for the time series of a firm forming the death of a director that cross-sits on the board of a product market peer. $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. The coefficient of $DeathTreated_{i,c} \times Post_{c,t}$ is the estimated effects of the death of a connected director. $\theta_{i,c}$ are firm times cohort fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. $DeathTreated_{i,c}$ is left out of the regressions as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A16: Cumulative abnormal returns (CARs) around announcement dates

	Average CARs	
	(1)	(2)
	Abnormal returns from the market model	Firm returns minus market returns as abnormal returns
Direct Connections	0.83%*	0.91%**
	(1.91)	(2.23)
Observations	396	396
Indirect Connections	0.73%*	0.62%*
	(1.89)	(1.71)
Observations	424	424
Other Appointments	0.23%***	0.22%***
	(4.29)	(4.23)
Observations	25,459	26,821

Note: This table reports the average CARs during a seven-day window around the announcement dates of director appointments. We report CARs both for appointments that cause board connections between product market peers to form and for all other appointments. In column (1), we estimate a market model using stock returns between [-300, -60] calendar days before the announcement dates and the CRSP NYSE/NYSEMKT/Nasdaq Value-Weighted Market Index. Then we calculate abnormal returns using our estimated model. In column (2), we calculate abnormal returns as firm returns minus market returns. We winsorize daily returns at the 1% and 99% percentiles before estimating the market model. We also winsorize CARs at the 1% and 99% percentiles. T-stats are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A17: Director network and convicted collusion cases

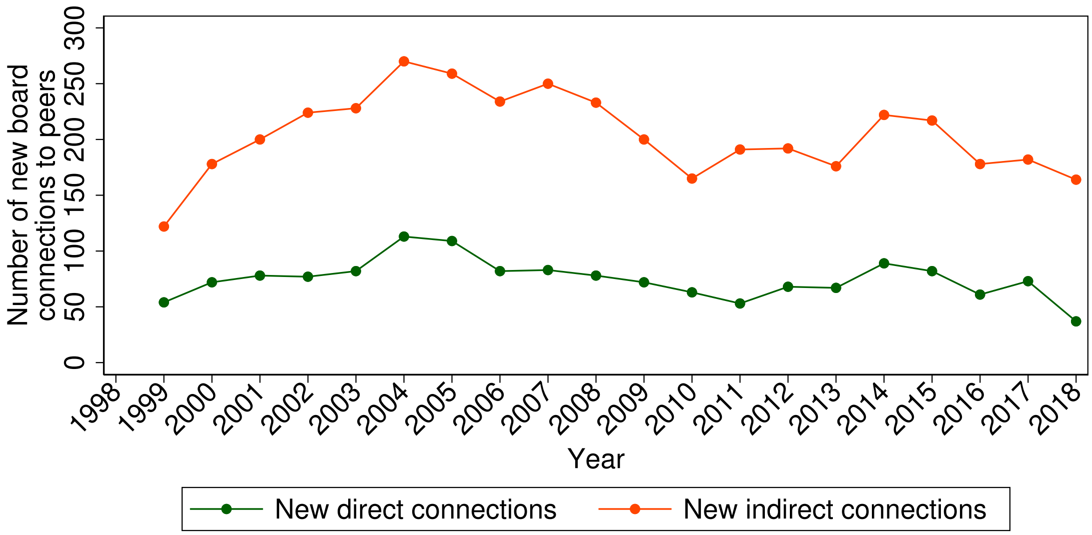
	(1) Prob. of active convicted collusion (%)	(2) Prob. of active convicted collusion (%)
Degree of separation = 0	0.058***	0.043**
	(3.22)	(2.39)
Degree of separation = 1	0.060***	0.053***
	(9.07)	(8.41)
Degree of separation = 2	0.017***	0.014***
	(12.21)	(10.93)
Degree of separation = 3	0.003***	0.002***
	(10.30)	(7.89)
Cosine similarity score		0.285***
		(10.91)
Is H-P peer		0.036***
		(5.73)
Observations	53,893,933	53,893,933
Year FE	No	Yes
Clustering	Firm-Pair	Firm-Pair
Adjusted R-squared	0.000	0.001

Note: This table reports estimates from the following Probit regression

$$\begin{aligned} \mathbb{1}(\text{Having an active convicted collusion scheme})_{i,j,t} &= \sum_{m=0}^{3} \beta_m \times \mathbb{1}(\text{Degree of separation is } m)_{i,j,t} \\ &+ Control_{i,j,t} + \theta_t + e_{i,j,t}. \end{aligned}$$

using the sample of firm-pairs with the degree of separation in the director network less than or equal to 4. Firm-pairs with a degree of separation of 4 serve as the omitted category. T-stats are in parentheses. Standard errors are clustered at the firm-pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

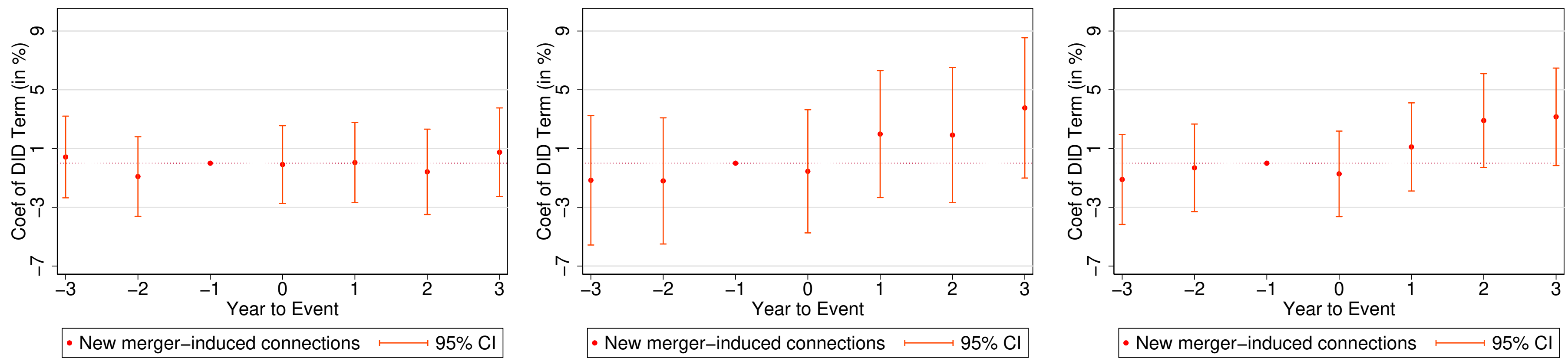
Figure A1: Distribution of new board connections over time



Note: This figure plots the number of new direct and indirect board connections in each year over our sample period of 1999-2018.

Figure A2: Plots of the dynamics of the difference between treated and control firms, using the merger-induced board connections

Panel A: Gross margin Panel B: Operating margin Panel C: ROA

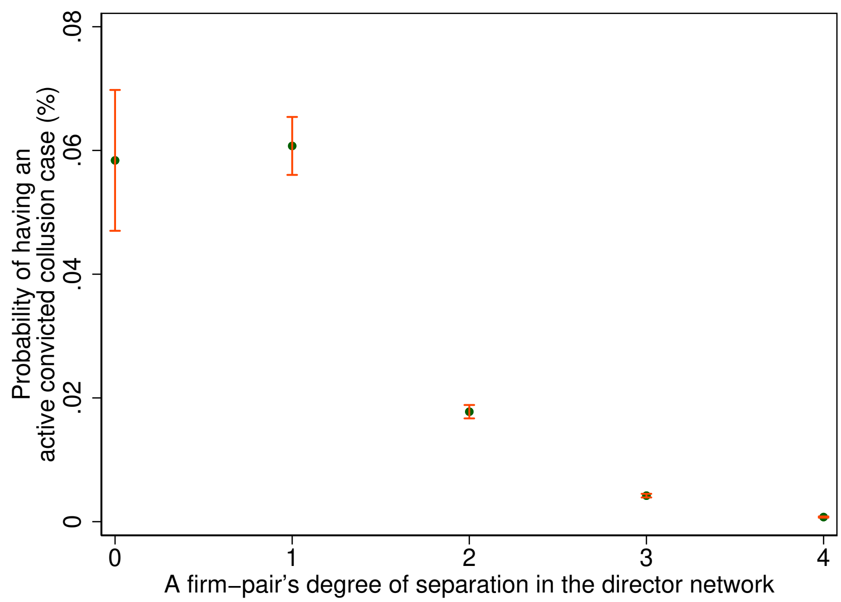


Note: This figure plots coefficients from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} \quad = & \quad \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
& + \quad MergerInducedTreated_{i,c} \times \left(\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} \right) + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

Here t represents the calendar year and τ represents the year relative to the treatment. $\mathbb{1}(\tau = s)_{c,t}$ is a dummy variable that is equal to one if the observation is $-s$ years before the treatment (for $s = -3, -2$) or if the observation is s years after the treatment (for $s = 0, 1, 2, 3$). We omit the dummy variables for the year prior to the event, i.e., $\tau = -1$, which forms the baseline year. Thus all the effects we document are relative to this year. The estimates of γ_s capture the difference in outcome variables between treated and control firms $-s$ years before the treatment (for $s = -3, -2$) or s years after the treatment (for $s = 0, 1, 2, 3$) relative to their differences in the baseline year. $MergerInducedTreated_{i,c}$ is left out of the regression as they are absorbed by $\theta_{i,c}$. Standard errors are clustered at the firm level.

Figure A3: Director network and convicted collusion cases



Note: This figure plots the probability of a firm-pair in a certain year being in an active convicted collusion case, conditional on each level of degree of separation between the firm-pair in the director network.

Figure A4: Dynamics under alternative matching schemes

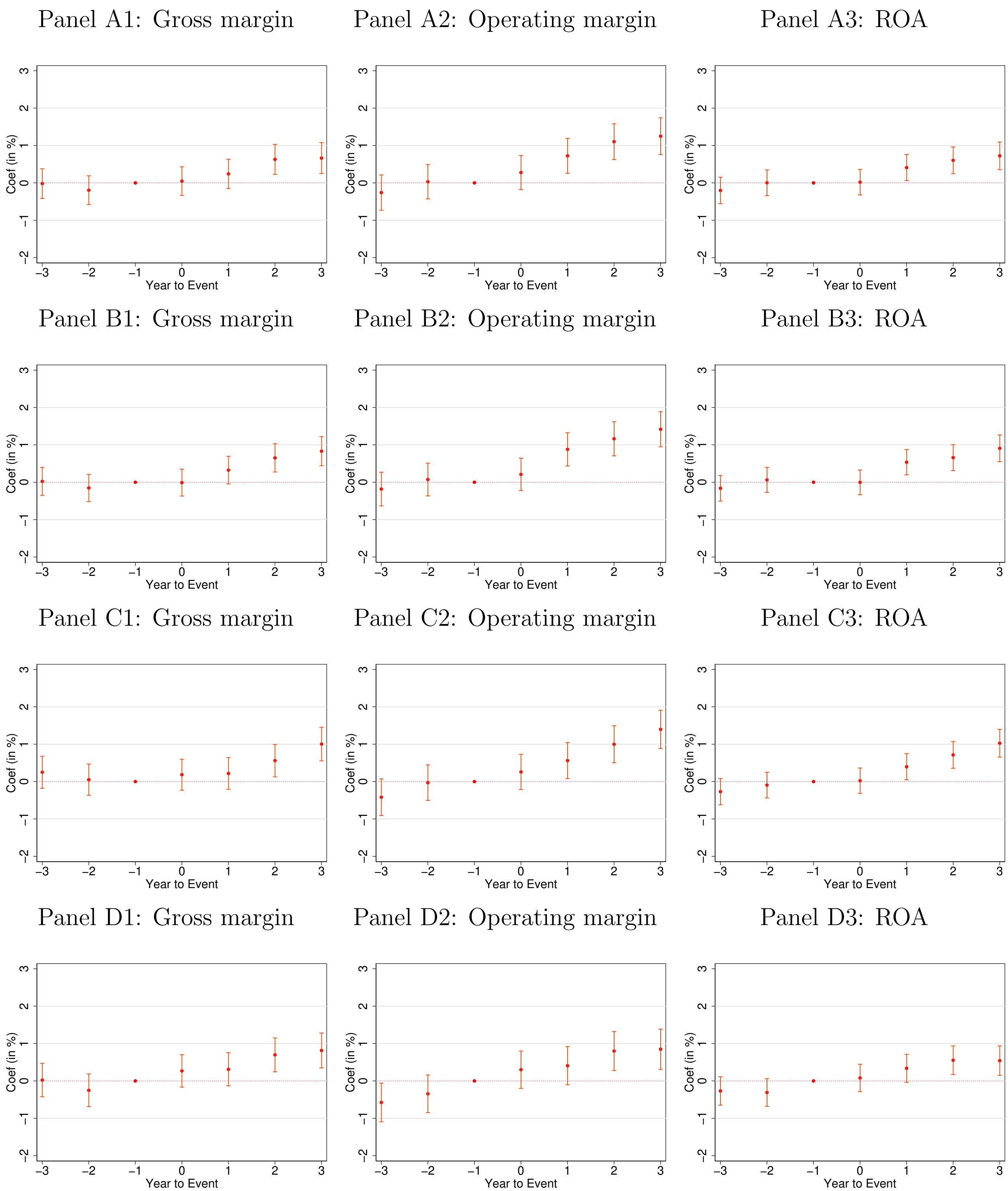
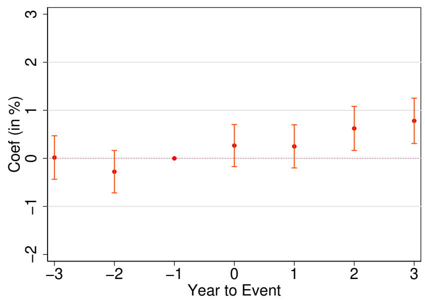
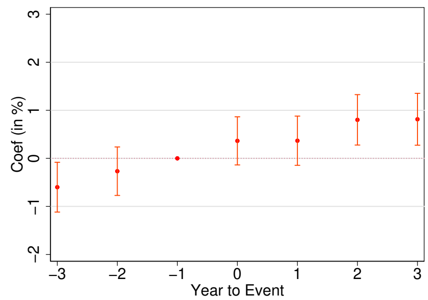


Figure A4: Dynamics under alternative matching

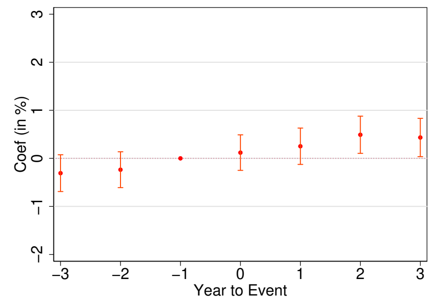
Panel E1: Gross margin



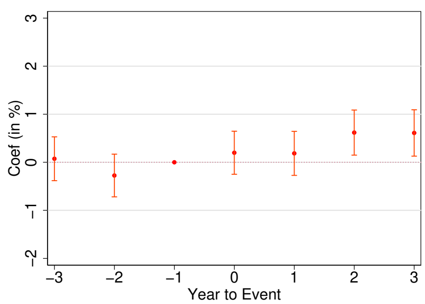
Panel E2: Operating margin



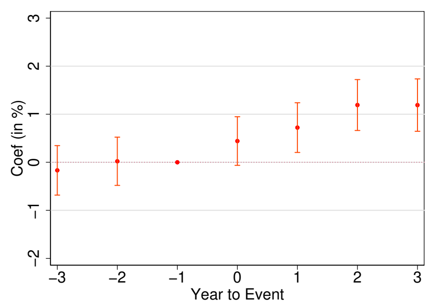
Panel E3: ROA



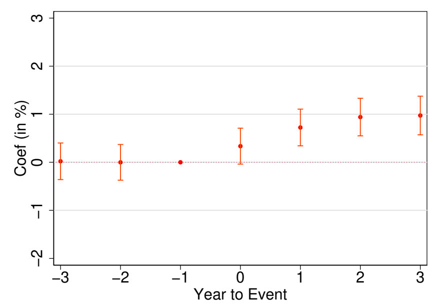
Panel F1: Gross margin



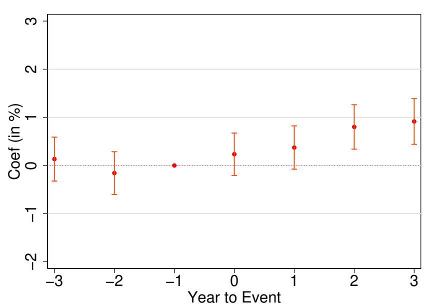
Panel F2: Operating margin



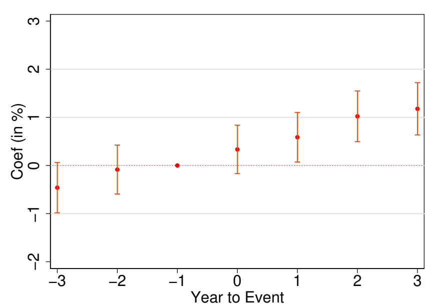
Panel F3: ROA



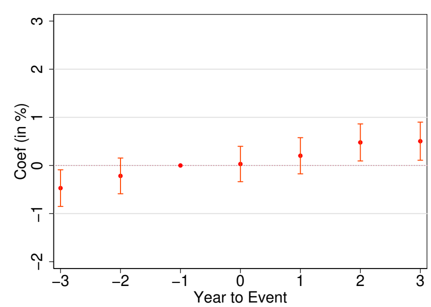
Panel G1: Gross margin



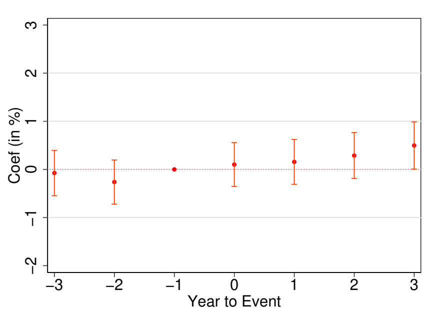
Panel G2: Operating margin



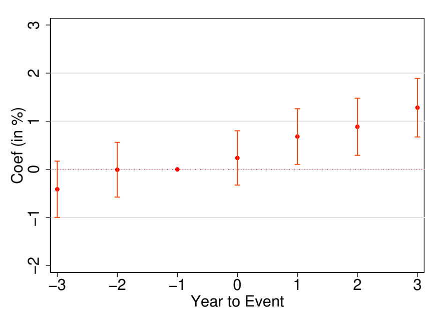
Panel G3: ROA



Panel H1: Gross margin



Panel H2: Operating margin



Panel H3: ROA

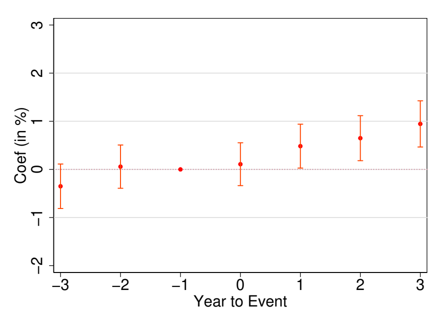
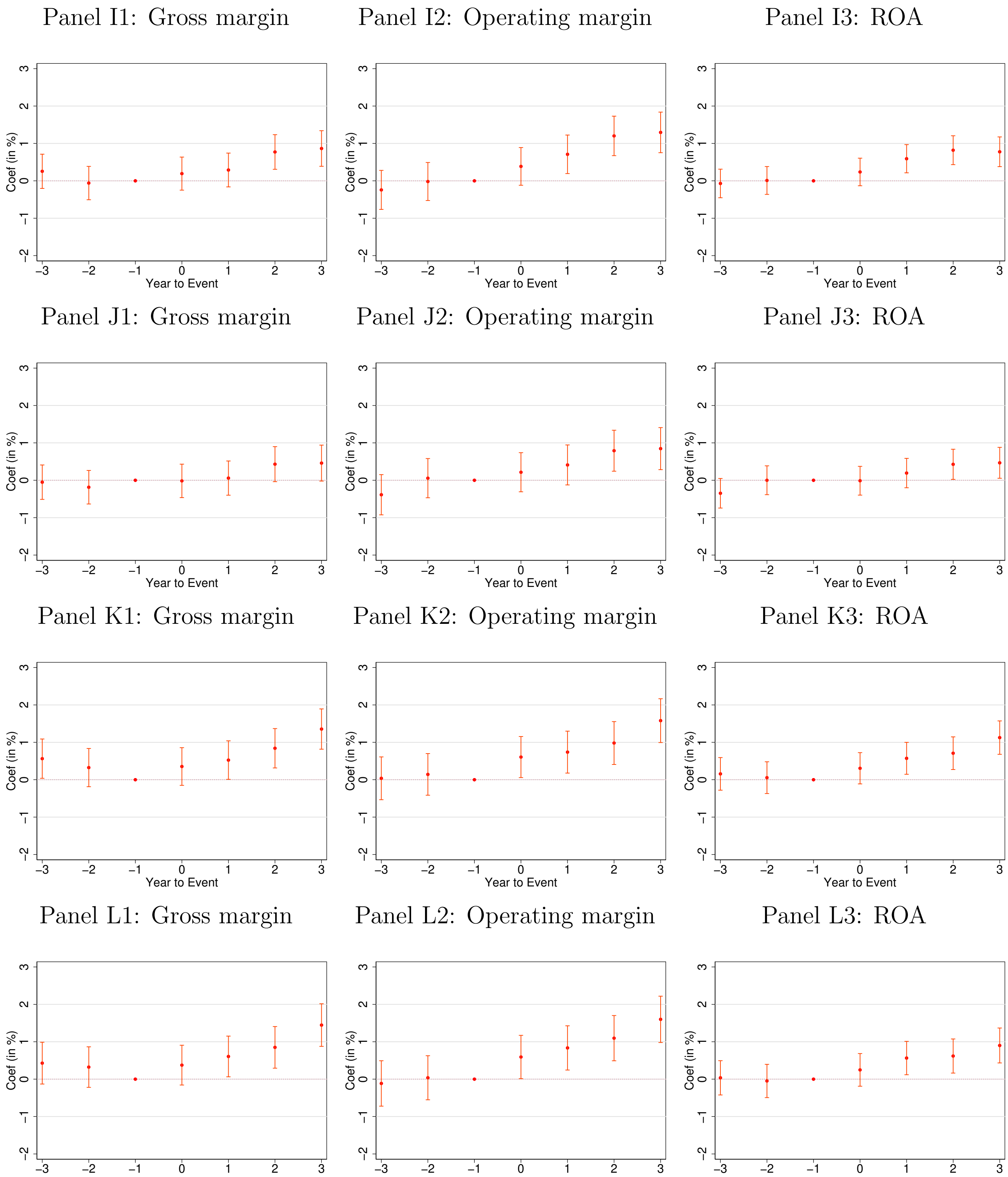


Figure A4: Dynamics under alternative matching



Note: This figure examines dynamics of the difference between treated and control firms under alternative matching schemes. Panels A-L correspond to the alternative matching schemes in Table A10.

IA.2 Definition of the non-focal-firm initiated subset of events

Changes on the board of the focal firm could be related to certain future prospects of this focal firm. Our non-focal-firm initiated subset of events aims to avoid such changes that can be directly linked to firm future prospects. In this section, we describe how we define and operationalize the non-focal-firm initiated subset of events.

We consider board connections that occur solely due to changes outside of the board of the focal firm. To identify this subset of events, we first identify the complement set of it, which is the set of events that occur at least partly due to changes on the board of the focal firm. Note that by definition new direct connections take place because of changes to the board of the focal firm (either appointing new directors or existing directors taking on roles at other firms), so our non-focal-firm initiated events only consider (a subset of) new indirect connections.

In particular, we consider that an event is *not* a non-focal-firm initiated one, if either:

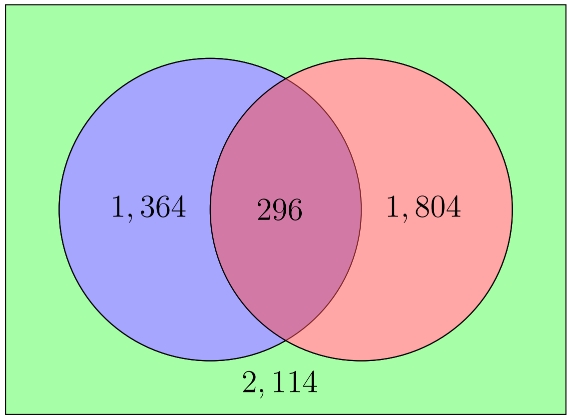
1. the appointment of new directors to the focal firm triggers new connections between the focal firm and its product market peers, and/or

2. new board positions taken by existing directors in the focal firm trigger new connections between the focal firm and its product market peers.

Taking out these *not* non-focal-firm initiated events from the set of all events, we get the subset of events that we deem to be non-focal-firm initiated. These events occur solely due to changes on the board of a third intermediate firm or a product market peer, and not due to any changes on the board of the focal firm.

We further decompose how the sample of all new connections relates to non-focal-firm initiated events with the following Venn diagram:

Figure A6: Definition of the non-focal-firm initiated subset of events



All events of new connections	5,578
Some new connections result from new appointment of directors to the focal firm	1,364 + 296 = 1,660
Some new connections result from existing directors on the focal firm's board taking on directorship elsewhere	1,804 + 296 = 2,100
New connections purely result from changes on boards of other firms (the non-focal-firm initiated subset of events)	2,114

IA.3 Director network and convicted collusion cases

We first plot in Internet Appendix Figure A3 the probability of a firm-pair having an active convicted collusion scheme in a certain year, conditional on the degree of separation of this firm-pair in the director network. We find that while this probability is around 0.06% for firm-pairs with a degree of separation of zero or one, it becomes 0.017% for firm-pairs with a degree of separation of two, and diminishes to near zero as the degree of separation further increases.

Next, we estimate the following probit model on this sample:

$$\begin{aligned} Prob(\text{Having an active convicted collusion scheme})_{i,j,t} &= \sum_{m=0}^{3} \beta_m \times \mathbb{1}(\text{Degree of separation is } m)_{i,j,t} \\ &+ Control_{i,j,t} + \theta_t + e_{i,j,t}, \end{aligned}$$

where i and j are indices for the pair firm i and firm j and t is the index for the calendar year. We report the findings in Internet Appendix Table A17. Column (1) reports the probability of having an active convicted collusion scheme, with firm-pairs of degree of separation of four being the baseline group. As firm-pairs closer in the director network might have more similar businesses, which can be a confounding factor that affects the tendency for anti-competitive practices, in column (2) we also control for the cosine similarity of the firm-pair's business descriptions as well as an indicator for whether the firm-pair is in the same Hoberg-Phillips industry. For both specifications, the associative relationship between the degree of separation in the director network and the probability of having an active collusion holds.

IA.4 Matching Nielsen Retail Scanner Data to BoardEx

We start by matching the Nielsen Retail Scanner Data (Nielsen) to producers in the GS1 Company Database. Universal Product Code (UPC) is the unit at which prices are recorded in Nielsen Retail Scanner Data, and the first 6-9 digits of it is a prefix that can identify the producer of the product. Each UPC-prefix corresponds to a unique producer. The GS1 Company Database records the name of each producer and the prefixes it owns. Following Baker et al. (2023), we start from the set of all UPCs in the Nielsen Retail Scanner Data and obtain their first 6-9 digits, which are our candidate UPC-prefixes. Then we search for these UPC-prefixes in the GS1 Company Database. While the length of a UPC-prefix can vary between 6 to 9, by the rule of its assignment, there will not be a longer UPC-prefix that contains a shorter UPC-prefix as its first many digits (Baker et al., 2023). Hence, if one of the four candidate prefixes for a UPC belongs to a producer in the GS1 Company Database, its producer can be uniquely pinned down. Out of 6,087,712 UPCs, we are able to find producer information for 4,695,783 of them.

Next, we match the producers in the GS1 Company Database to BoardEx. As there is no common identifier among these two databases, we match by the name string. First, we perform an exact match of firm names in the GS1 Company Database to firm names in BoardEx. We clean the firm names by dropping suffixes such as "Co", "Inc", and "Corp" and removing special characters. Second, we use WRDS Company Subsidiary Data to identify subsidiaries of firms in BoardEx and then we do an exact match of firm names in the GS1 Company Database that are still not matched in the prior step to the names of subsidiaries of firms in BoardEx. Third, for the remaining unmatched firm names in the GS1 Company Database, we conduct a fuzzy match between them and firms in BoardEx. We manually check the results from the fuzzy match and make sure we only retain correct matches. Finally, we manually check the top 1,000 UPC-prefixes with the most sales and see if they can be matched to a firm in BoardEx. In this step, we employ Google search and also the location information that is provided in the GS1 Company Database.

We are able to match 2,715,025 UPCs to a firm in BoardEx, which account for 44.6% of all UPCs and 63.4% of the total sales in Nielsen.